

# **Safety Quantification for Nonlinear and Time-Delay Systems using Occupation Measures**

---

Author: **Jared Miller**

Committee: Octavia Camps

Didier Henrion (LAAS-CNRS)

Bahram Shafai

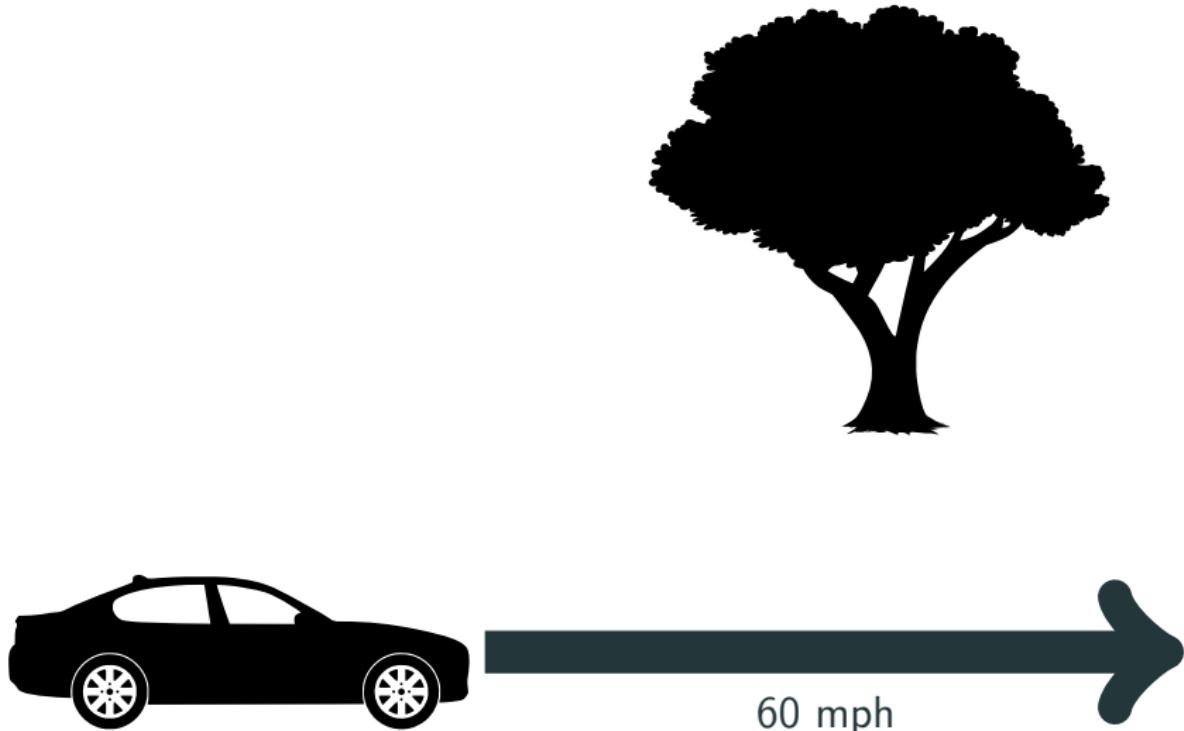
Eduardo Sontag

**Mario Sznaier**

April 3, 2023



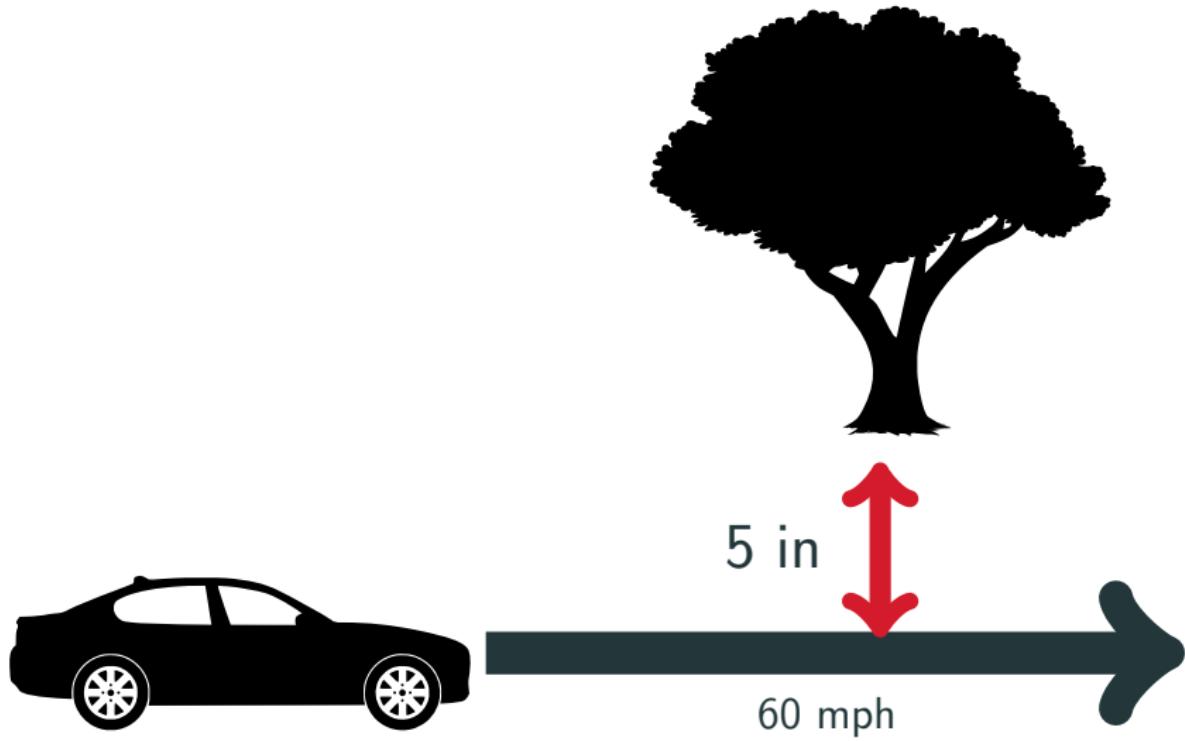
# Safety Example



## Safety Example (Barrier/Density Function)

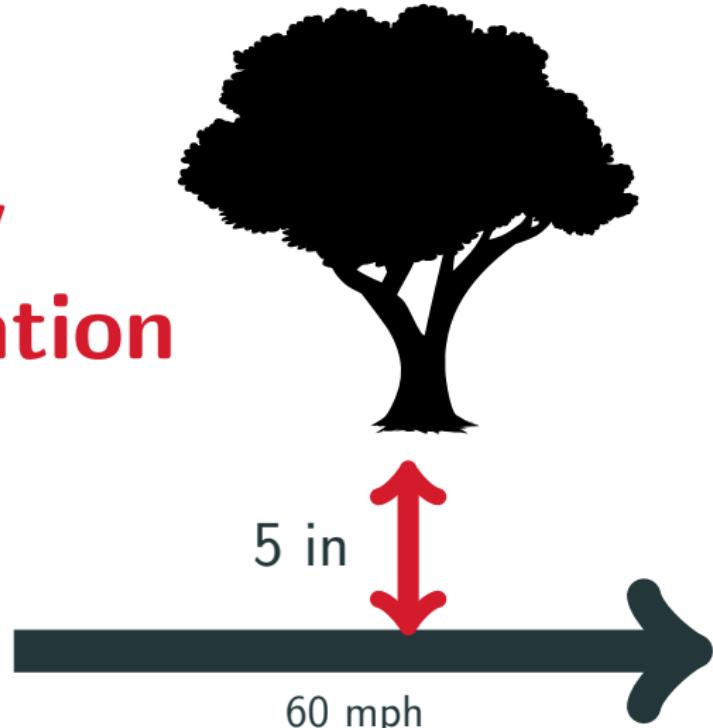


## Safety Example (Distance Estimate)

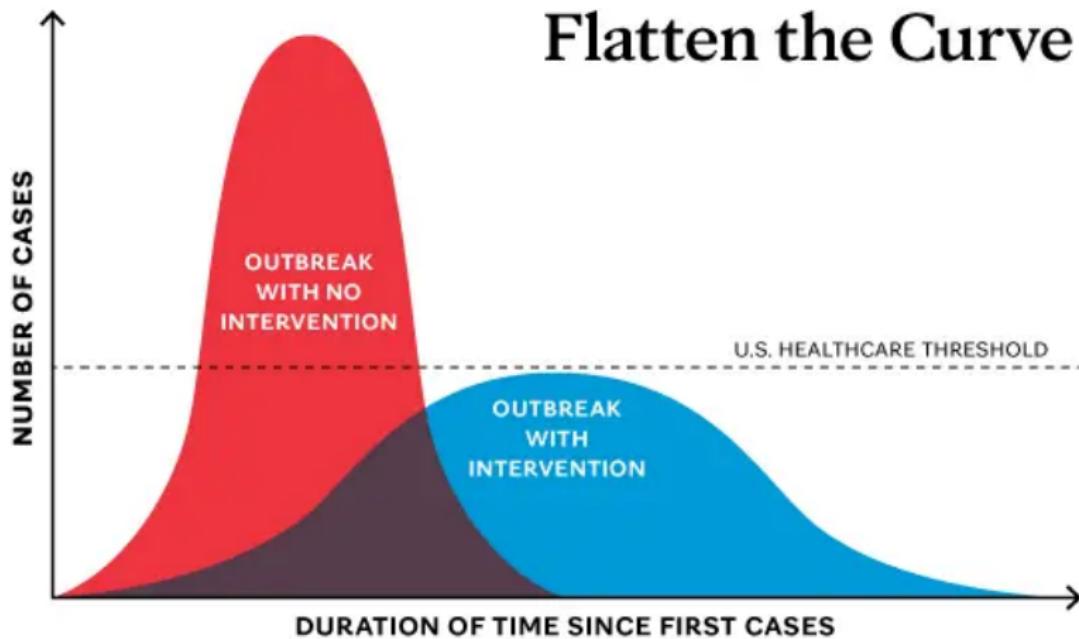


## Safety Example

# Safety Quantification



# Motivation: Epidemic

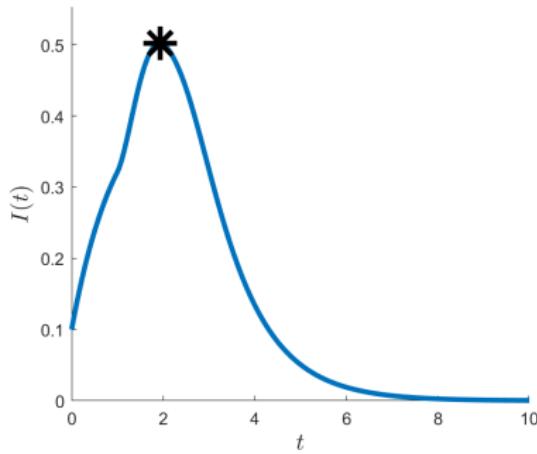


Adapted from CDC

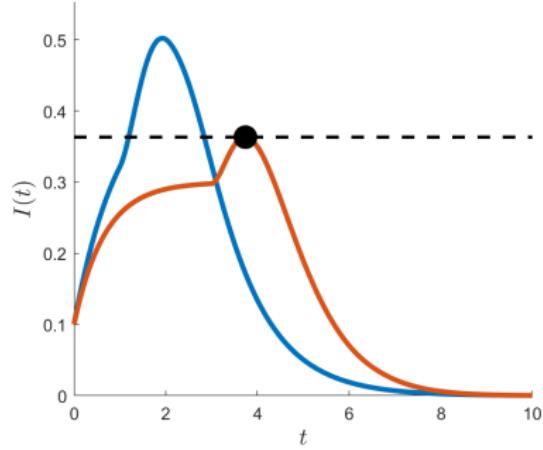
Image credit to Mayo Clinic News Network

# Problems Covered

## Peak Estimation



## Peak-Minimizing Control



# Main Ideas

---

Pose safety quantification problems

Want convex, convergent, bisection-free algorithms

Formulate using convex linear programs in measures

Increasing-quality bounds using Semidefinite Programming

# Overview of Presentation

---

Peak estimation background

1. Survey of Thesis Work
2. Peak Value-at-Risk Estimation
3. Time-Delay Systems

Wrap-up

# Peak Estimation Background

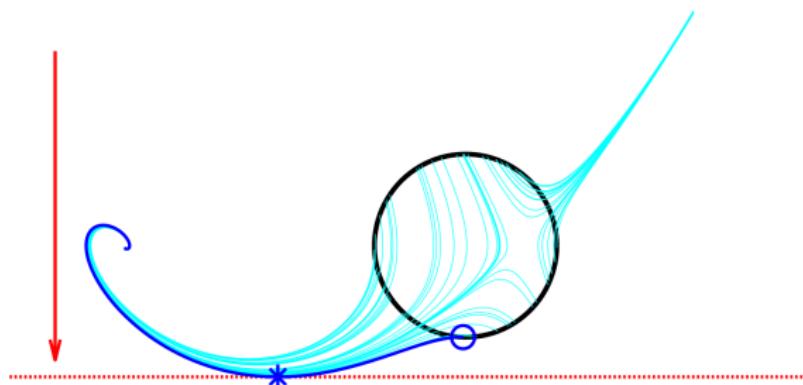
---

# Peak Estimation Background

Find extreme value of  $p(x)$  along trajectories

$$P^* = \sup_{t, x_0 \in X_0} p(x(t | x_0))$$

$$\dot{x}(t) = f(t, x(t)) \quad \forall t \in [0, T], \quad x(0) = x_0.$$



$$p(x) = -x_2, \quad \dot{x} = [x_2, -x_1 - x_2 + x_1^3/3]$$

# Occupation Measure

Time trajectories spend in set

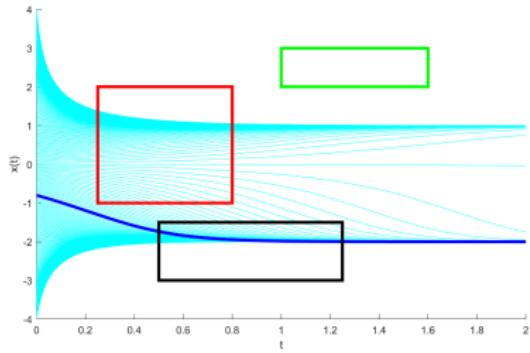
Test function

$$v(t, x) \in C([0, T] \times X)$$

Single trajectory:

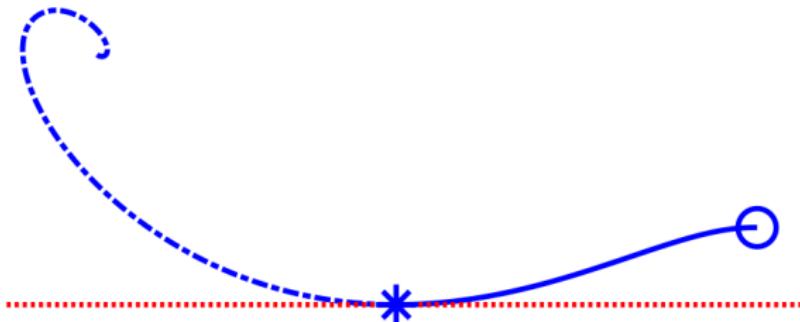
$$\langle v, \mu \rangle = \int_0^T v(t, x(t | x_0)) dt$$

Averaged trajectory:  $\langle v, \mu \rangle = \int_X \left( \int_0^T v(t, x) dt \right) d\mu_0(x)$



$$x' = -x(x+2)(x-1)$$

# Connection to Measures



Measures: Initial  $\mu_0$ , Peak  $\mu_p$ , Occupation  $\mu$

For all functions  $v(t, x) \in C([0, T] \times X)$

$$\mu_0^* : \quad \langle v(0, x), \mu_0^* \rangle = v(0, x_0^*)$$

$$\mu_p^* : \quad \langle v(t, x), \mu_p^* \rangle = v(t_p^*, x_p^*)$$

$$\mu^* : \quad \langle v(t, x), \mu^* \rangle = \int_0^{t_p^*} v(t, x^*(t | x_0^*)) dt$$

# Liouville Equation

Lie derivative (instantaneous change along  $f$ )  $\forall v \in C^1$ :

$$\mathcal{L}_f v = \partial_t v(t, x) + f(t, x) \cdot \nabla_x v(t, x) \quad (1a)$$

Conservation law: final = initial + accumulated change

$$\langle v(t, x), \mu_p \rangle = \langle v(0, x), \mu_0 \rangle + \langle \mathcal{L}_f v(t, x), \mu \rangle \quad (1b)$$

$$\mu_p = \delta_0 \otimes \mu_0 + \mathcal{L}_f^\dagger \mu \quad (1c)$$

Liouville ‘represents’ dynamics  $\dot{x}(t) = f(t, x(t))$

# Measures for Peak Estimation

Infinite-dimensional Linear Program (Cho, Stockbridge, 2002)

$$p^* = \sup \langle p(x), \mu_p \rangle \quad (2a)$$

$$\langle 1, \mu_0 \rangle = 1 \quad (2b)$$

$$\langle v(t, x), \mu_p \rangle = \langle v(0, x), \mu_0 \rangle + \langle \mathcal{L}_f v(t, x), \mu \rangle \quad \forall v \quad (2c)$$

$$\mu, \mu_p \in \mathcal{M}_+([0, T] \times X) \quad (2d)$$

$$\mu_0 \in \mathcal{M}_+(X_0) \quad (2e)$$

Instance of Optimal Control Program (Lewis and Vinter, 1980)

$(\mu_0^*, \mu_p^*, \mu^*)$  is feasible with  $P^* = \langle p(x), \mu_p^* \rangle \leq p^*$

$P^* = p^*$  if compactness, Lipschitz properties hold

# Moments for Peak Estimation

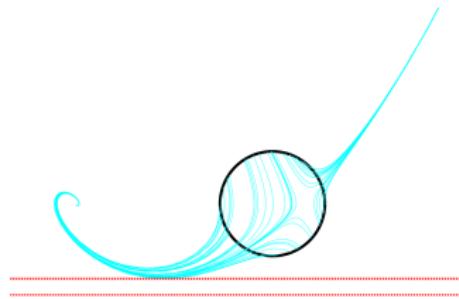
Moment:  $y_\alpha = \langle x^\alpha, \nu \rangle \quad \forall \alpha \in \mathbb{N}^n$

Moment matrix  $\mathbb{M}[y]_{\alpha\beta} = y_{\alpha+\beta}$  is PSD

$$\mathbb{M}_2[y] = \begin{bmatrix} y_{00} & y_{10} & y_{01} & y_{20} & y_{11} & y_{02} \\ y_{10} & y_{20} & y_{11} & y_{30} & y_{21} & y_{12} \\ y_{01} & y_{11} & y_{02} & y_{21} & y_{12} & y_{03} \\ y_{20} & y_{30} & y_{21} & y_{40} & y_{31} & y_{11} \\ y_{11} & y_{21} & y_{12} & y_{31} & y_{22} & y_{13} \\ y_{02} & y_{12} & y_{03} & y_{22} & y_{13} & y_{04} \end{bmatrix} \succeq 0$$

Liouville induces affine relation in  $(\mu^0, \mu^p, \mu) \rightarrow (y^0, y^p, y)$

# Peak Estimation Example Bounds



Converging bounds to min.  $x_2 = -0.5734$  (moment-SOS)

Box region  $X = [-2.5, 2.5]$ , time  $t \in [0, 5]$

Max. PSD size:  $\binom{(n+1)+(d+\lfloor \deg f/2 \rfloor)}{n+1}$  (Fantuzzi, Goluskin, 2020)

# **Survey of Thesis Work**

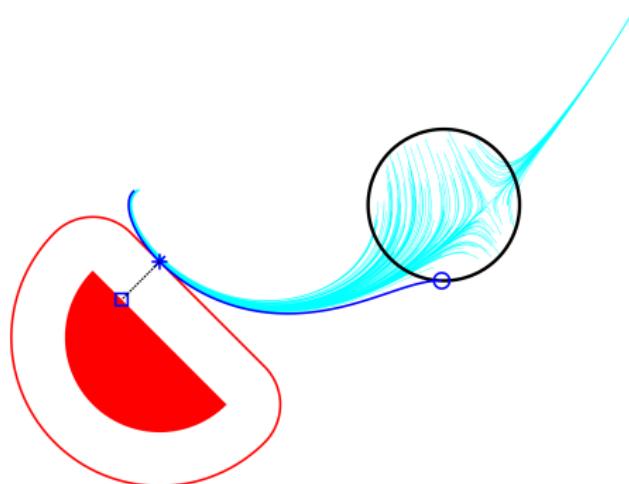
---

# Distance Estimation Problem

Unsafe set  $X_u$ , point-set distance  $c(x; X_u) = \inf_{y \in X_u} c(x, y)$

$$P^* = \inf_{t, x_0 \in X_0} c(x(t \mid x_0); X_u)$$

$$\dot{x}(t) = f(t, x(t)) \quad \forall t \in [0, T], \quad x(0) = x_0.$$



$L_2$  bound of 0.2831

# Distance Program (Measures)

Infinite Dimensional Linear Program (Convergent)

$$p^* = \inf \langle c(x, y), \eta(x, y) \rangle \quad (3a)$$

$$\langle 1, \mu_0 \rangle = 1 \quad (3b)$$

$$\langle v(t, x), \mu_p \rangle = \langle v(0, x), \mu_0 \rangle + \langle \mathcal{L}_f v(t, x), \mu \rangle \quad \forall v \quad (3c)$$

$$\langle w(x), \eta(x, y) \rangle = \langle w(x), \mu_p(t, x) \rangle \quad \forall w \quad (3d)$$

$$\eta \in \mathcal{M}_+(X \times X_u) \quad (3e)$$

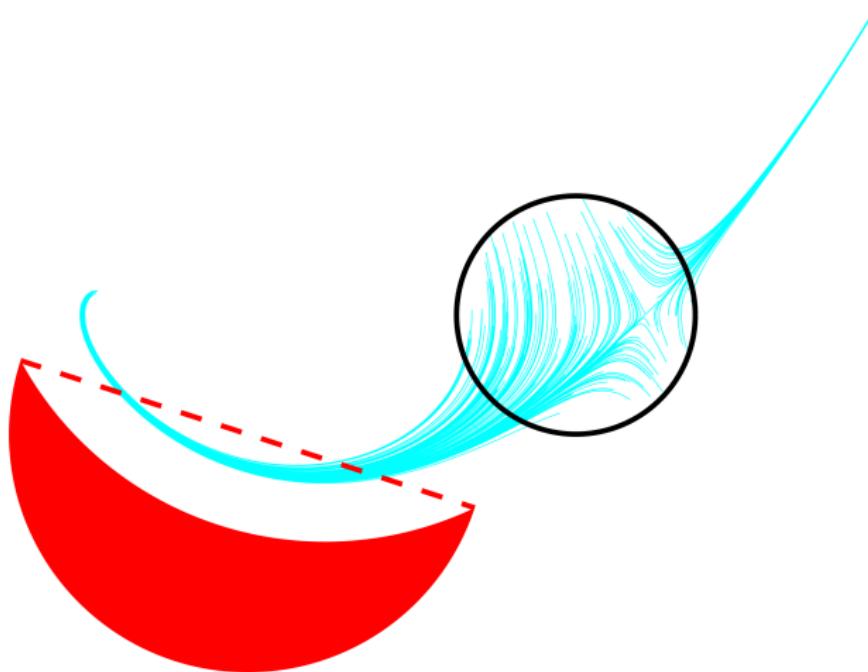
$$\mu_p, \mu \in \mathcal{M}_+([0, T] \times X) \quad (3f)$$

$$\mu_0 \in \mathcal{M}_+(X_0) \quad (3g)$$

Probability measures:  $(\mu_0, \mu_p, \eta)$

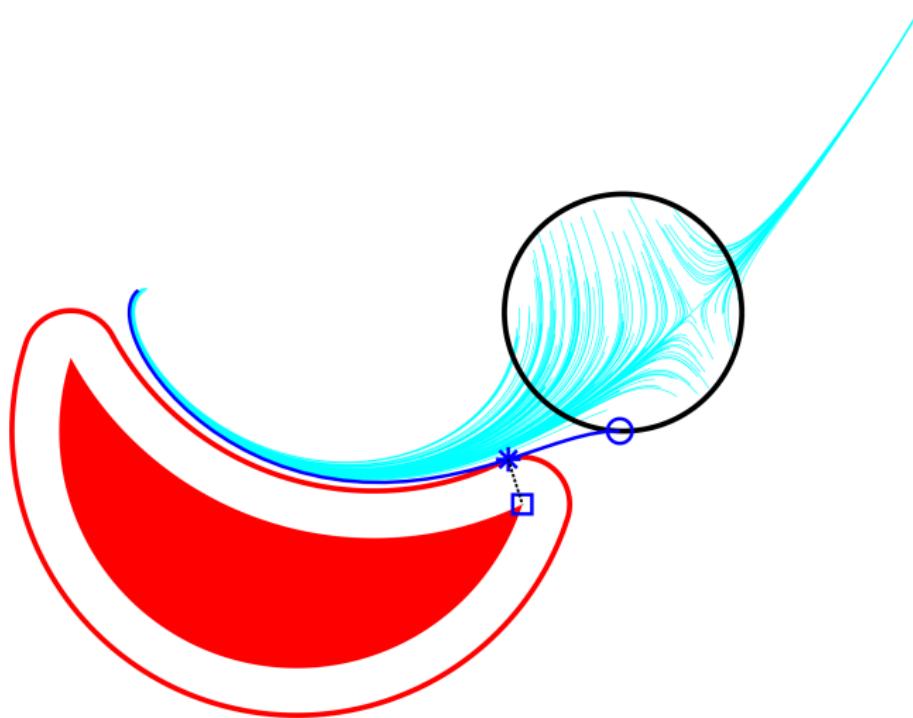
Near-optimal trajectories if moment-matrix  $\approx$  rank-1

# Distance Example (Flow Moon)



Collision if  $X_u$  was a half-circle

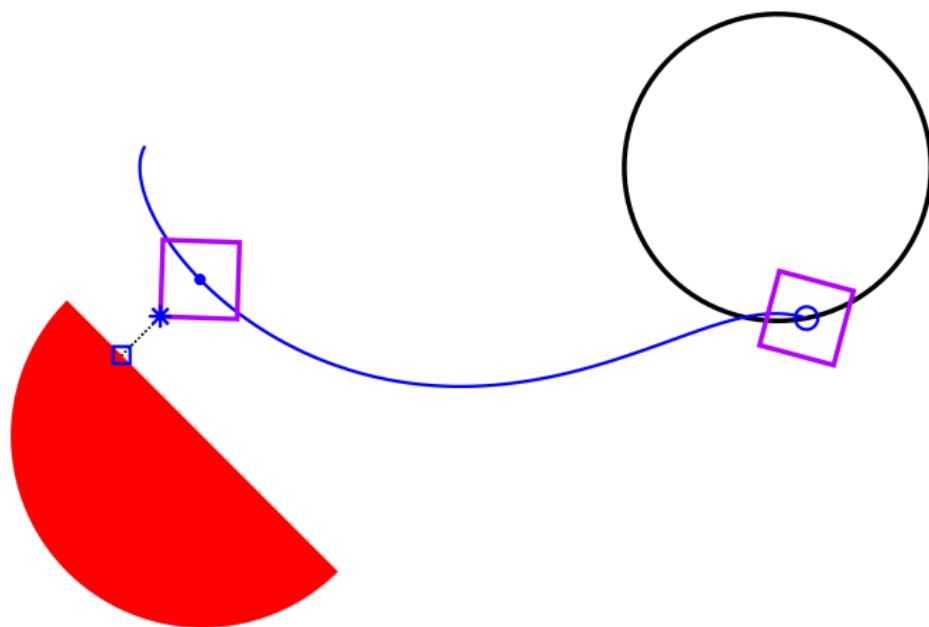
# Distance Example (Flow Moon)



$L_2$  bound of 0.1592

# Safety of Shapes

Points on shape  $S$  with orientation  $\omega$  (e.g., rigid body motion)

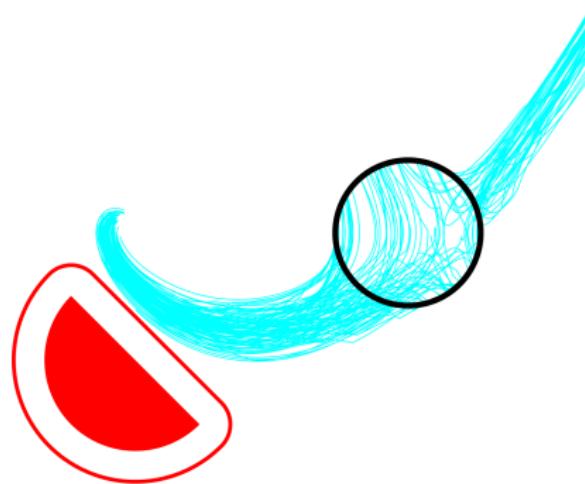


$L_2$  bound of 0.1465, rotating square

# Distance with Bounded Uncertainty

Dynamics  $\dot{x}(t) = f(t, x(t), w(t))$  with  $w(t) \in W$

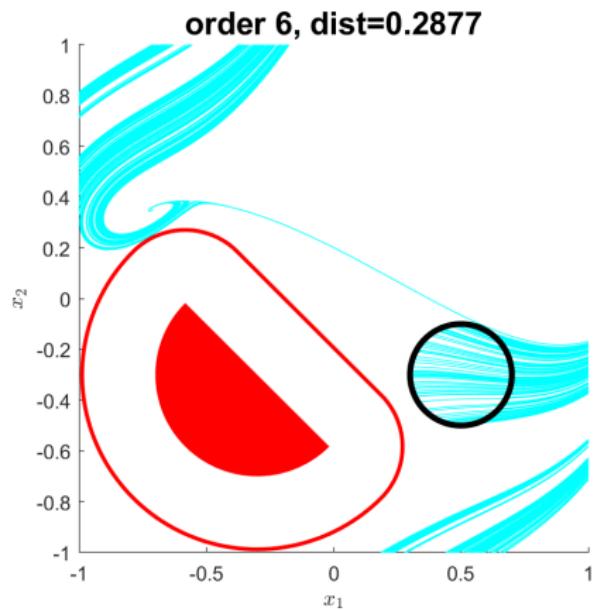
Young measure  $\mu(t, x, w)$ , Liouville term  $\langle \mathcal{L}_f v(t, x, w), \mu \rangle$



$L_2$  bound of 0.1691,  $w(t) \in [-1, 1]$

# Hybrid Systems

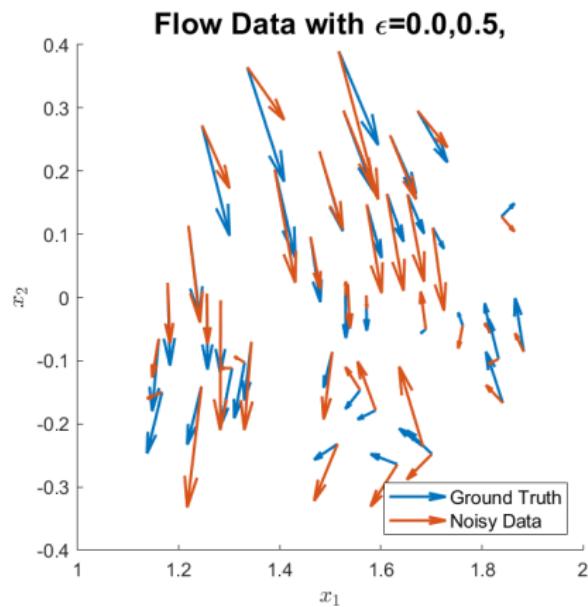
Continuous dynamics with discrete jumps/transitions



$$R_{\text{left} \rightarrow \text{bottom}} = [1 - x_2; x_1], \quad R_{\text{right} \rightarrow \text{top}} = [x_2; x_1]$$

# Sampling: Flow System

Data  $\mathcal{D} = \{(t_j, x_j, \dot{x}_j)\}_j$  under mixed  $L_\infty$ -bounded noise



$$\dot{x} = [x_2, -x_1 - x_2 + x_1^3/3]$$

# Dynamics Model

Given data  $\mathcal{D}$ , budget  $\epsilon$ , system model  $\{f_0, f_\ell\}$

Parameterize ground truth  $F$  by functions in dictionary

$$\dot{x}(t) = f(t, x, w) = f_0(t, x) + \sum_{\ell=1}^L w_\ell f_\ell(t, x)$$

Ground truth satisfies corruption  $J(w^*) \leq \epsilon$

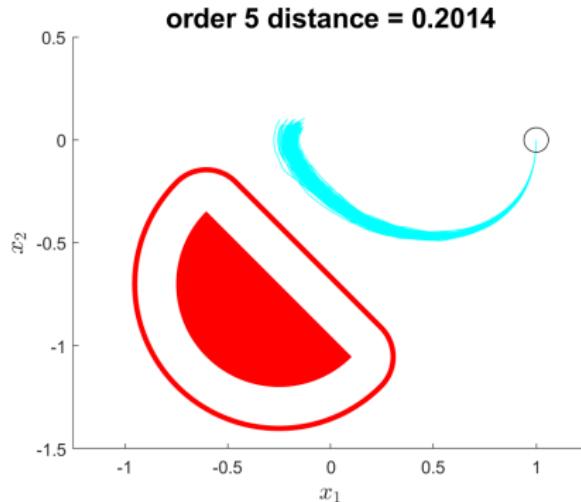
$L_\infty$  example:  $J(w) = \max_j \|f(t_j, x_j, w) - \dot{x}_j\|_\infty$

# Distance Estimation Example (Flow)

Input-affine + Semidefinite Representable uncertainty

$$\mathcal{L}_f v(t, x, w) \leq 0 \quad \forall (t, x, w) \in [0, T] \times X \times W$$

PSD Size 8568  $\rightarrow$  56 ( $L = 10$ ) using robust counterparts



$$\dot{x} = [x_2, \text{cubic}(x_1, x_2)]$$

# Crash-Safety

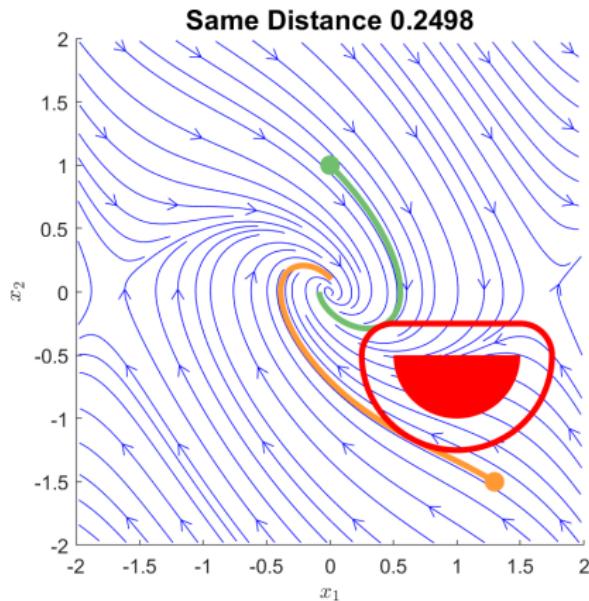
How much data corruption is needed to crash?

$$Q^* = \inf_{t^*, x_0, w} \left[ \sup_{t \in [0, t^*]} J(w(t)) \right]$$
$$\dot{x}(t) = f(t, x(t), w(t)) \quad \forall t \in [0, t^*]$$
$$x(t \mid x_0, w(\cdot)) \in X_u$$
$$w(\cdot) \in W, \quad t^* \in [0, T], \quad x_0 \in X_0$$

Model safe if  $Q^* > \epsilon$

# Example Crash-Bounds

Two trajectories have same distance, different crash-bounds



Green-Top  $Q^* = 0.316$ , Yellow-Bottom  $Q^* = 0.622$

# Peak-Minimizing Control

Add state  $\dot{z} = 0$  (Molina, Rapaport, Ramírez 2022)

$$Q_z^* = \inf_{t^*, x_0, z, w} z \quad (4a)$$

$$\dot{x}(t) = f(t, x(t), w(t)) \quad \forall t \in [0, t^*] \quad (4b)$$

$$\dot{z}(t) = 0 \quad \forall t \in [0, t^*] \quad (4c)$$

$$J(w(t)) \leq z \quad \forall t \in [0, t^*] \quad (4d)$$

$$x(t^* | x_0, w(\cdot)) \in X_u \quad (4e)$$

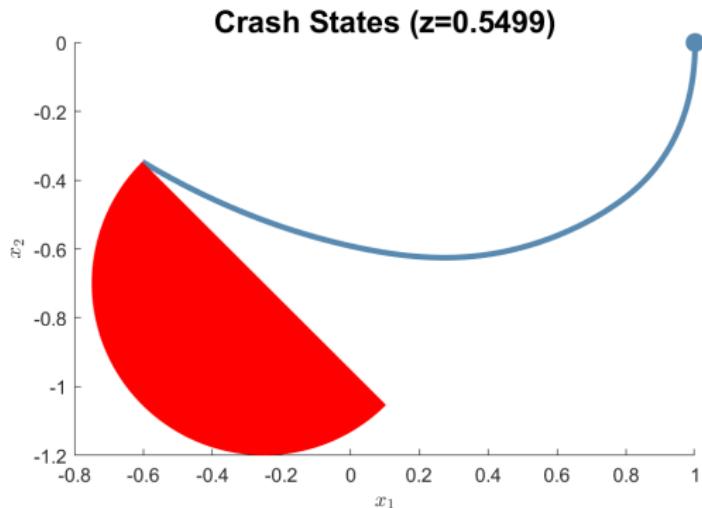
$$w(\cdot) \in W, t^* \in [0, T] \quad (4f)$$

$$x_0 \in X_0, z \in [0, J_{\max}] \quad (4g)$$

Equivalent formulation,  $Q^* = Q_z^*$

# Data-Driven Flow Crash-Bound

CasADI matches degree-4 moment-SOS crash bound



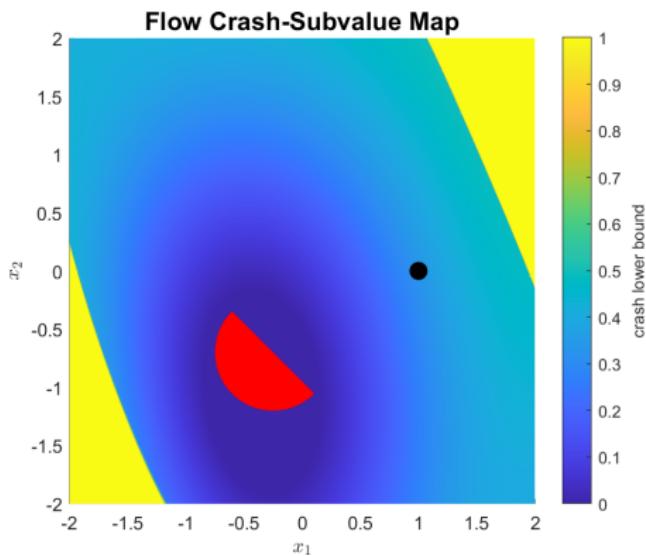
Terminal measure  $\mu_p \in \mathcal{M}_+([0, T] \times X_u)$

True  $\epsilon = 0.5 < 0.5499$ , distance  $\approx 0.2014$

# Flow Crash-Subvalue

Piecewise-polynomial subvalue for crash-safety

Based on Joint+Marginal optimization (Lasserre, 2010)



Bound of  $0.3399 \leq 0.5499$ , but valid everywhere in  $X$

# **Peak Value-at-Risk Estimation**

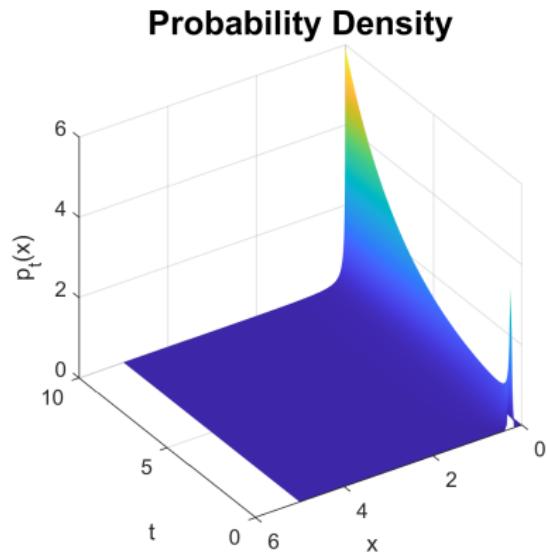
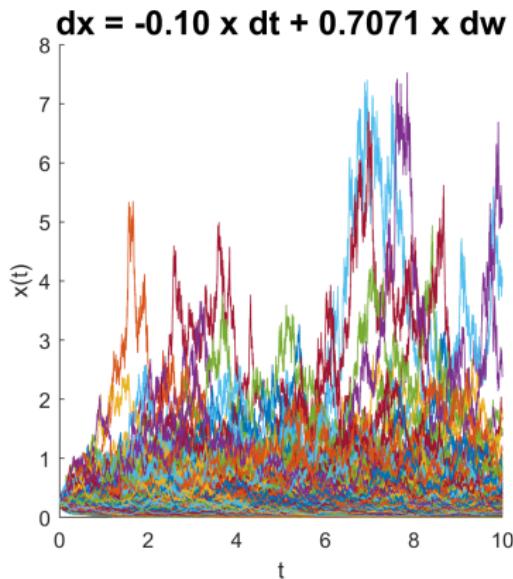
**with M. Tacchi, M. Sznajer, A. Jasour**

---

# Stochastic Differential Equation

Multivariate SDE  $dx = f(t, x)dt + g(t, x)dw$  (Itô)

Drift  $f$  and Diffusion  $g$

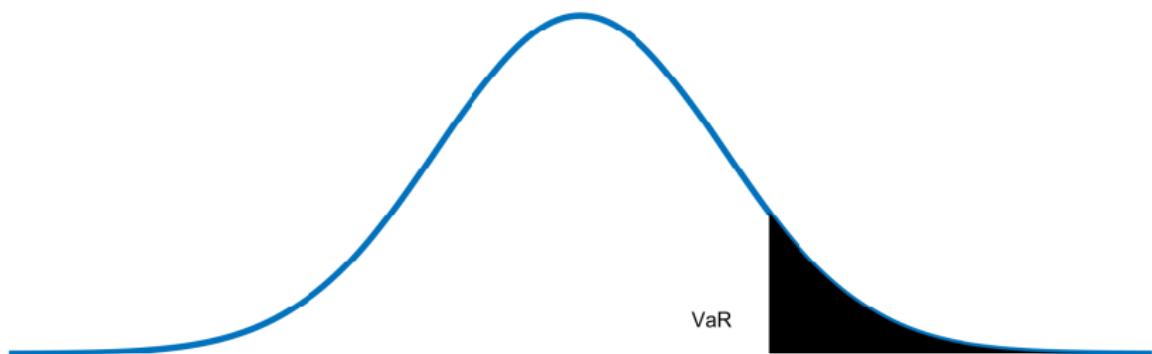


Geometric Brownian Motion

## Value-at-Risk (Quantile)

$\epsilon$ -VaR of univariate measure  $\omega(q)$  is unique number with

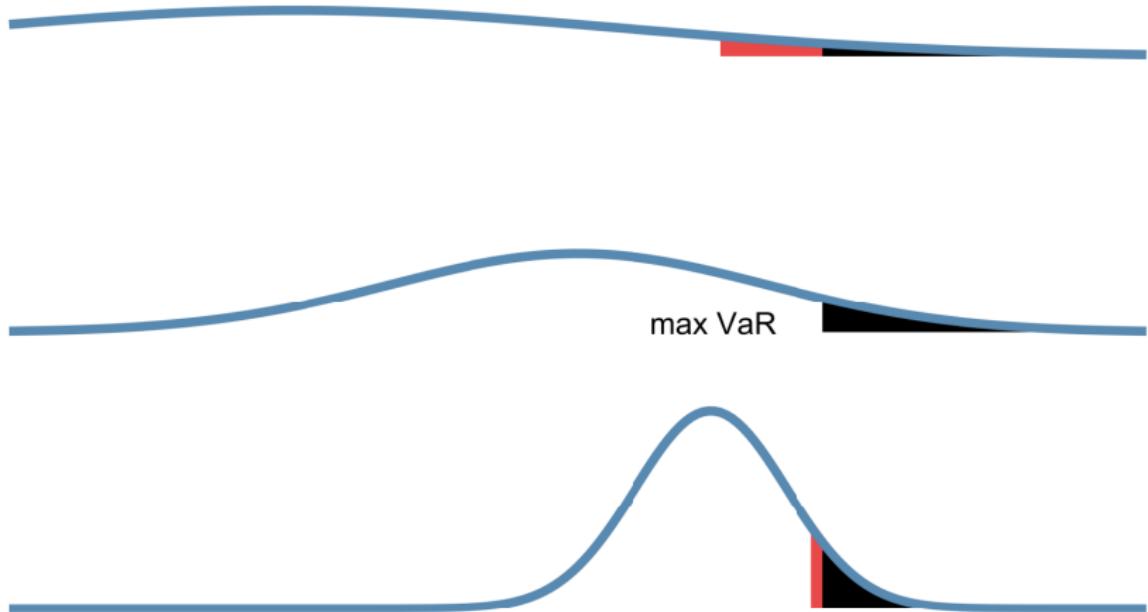
$$\text{Prob}_{\omega}(q \geq \text{VaR}_\epsilon(\omega)) = \epsilon$$



$\text{VaR} = 1.282$  for unit normal distribution at  $\epsilon = 10\%$

# Maximal Value at Risk

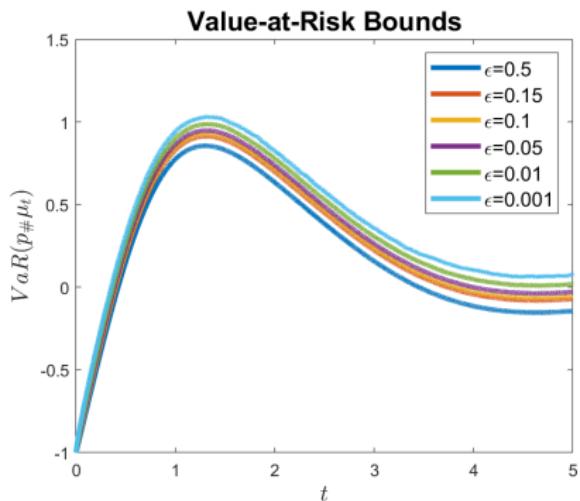
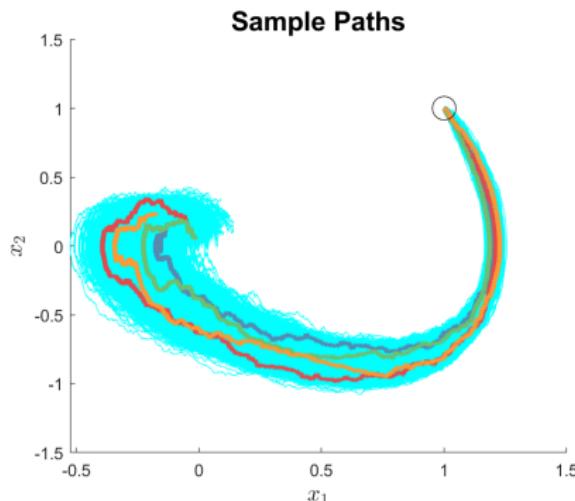
Maximize  $\epsilon$ -VaR among multiple distributions



Red + Black areas = 10% probability

# Value-at-Risk Example (Monte Carlo)

50,000 samples with  $T = 5$ ,  $\Delta t = 10^{-3}$



VaR of  $p = -x_2$  along  $dx = \begin{bmatrix} x_2 \\ -x_1 - x_2 - \frac{1}{2}x_1^3 \end{bmatrix} dt + \begin{bmatrix} 0 \\ 0.1 \end{bmatrix} dw$

# Chance-Peak Problem

Maximize VaR of  $p(x)$  along SDE trajectories

$p_{\#}\mu_{t^*}$  : distribution of  $p(x(t))$  at time  $t^*$

$$P^* = \sup_{t^* \in [0, T]} \text{VaR}_\epsilon(p_{\#}\mu_{t^*}) \quad (5a)$$

$$dx = f(t, x)dt + g(t, x)dw \quad (5b)$$

$$\text{stopping time of } \min(t^*, \text{exit from } X) \quad (5c)$$

$$x(0) \sim \mu_0. \quad (5d)$$

# Value-at-Risk Bounds

Concentration inequalities can upper-bound VaR

$$VaR_\epsilon(\omega) \leq \text{stdev}(\omega)r + \text{mean}(\omega)$$

Name	$r$	Condition
Cantelli	$\sqrt{1/(\epsilon) - 1}$	$\omega$ probability distribution
VP	$\sqrt{4/(9\epsilon) - 1}$	$\omega$ unimodal, $\epsilon < 1/6$

Coherent Risk Measures (e.g., CVaR) can also bound VaR

# Concentration-Bounded Chance-Peak

Apply concentration inequalities to get upper bound  $P_r^* \geq P^*$

Objective upper-bounds VaR w.r.t. time- $t^*$  distribution  $\mu_{t^*}$

$$P_r^* = \sup_{t^* \in [0, T]} r\sqrt{\langle p^2, \mu_{t^*} \rangle - \langle p, \mu_{t^*} \rangle^2} + \langle p, \mu_{t^*} \rangle \quad (6a)$$

$$dx = f(t, x)dt + g(t, x)dw \quad (6b)$$

stopping time of  $\min(t^*, \text{exit from } X)$  (6c)

$$x(0) \sim \mu_0. \quad (6d)$$

Max-Mean:  $\epsilon = 0.5$ ,  $r = 0$  (Cho, Stockbridge, 2002)

# Occupation Measure Formulation

Occupation measure  $\mu$ , terminal measure  $\mu_\tau$

Second-Order Cone Program in measures (3d SOC)

$$p_r^* = \sup r \sqrt{\langle p^2, \mu_\tau \rangle - \langle p, \mu_\tau \rangle^2} + \langle p, \mu_\tau \rangle \quad (7a)$$

$$\mu_\tau = \delta_0 \otimes \mu_0 + \mathcal{L}^\dagger \mu \quad (7b)$$

$$\mu_\tau, \mu \in \mathcal{M}_+([0, T] \times X) \quad (7c)$$

Generator  $\mathcal{L}v = \partial_t v + f \cdot \nabla_x v + g^T (\nabla_{xx}^2 v) g / 2$  (Dynkin's)

Results in upper-bound  $p_r^* \geq P_r^* \geq P^*$ , use moments

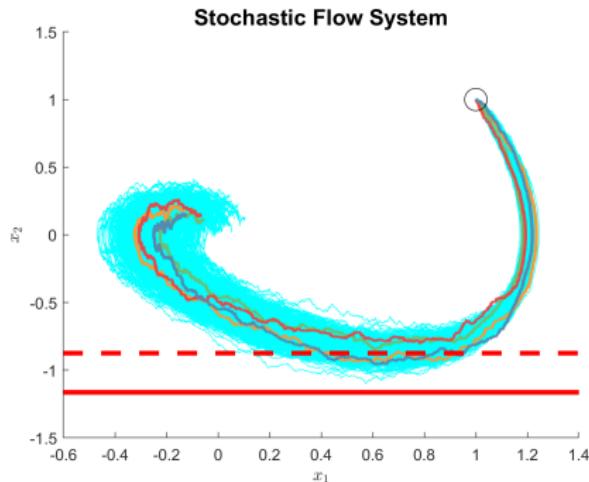
# Chance-Peak Examples

---

## Two-State

Stochastic Flow system from Prajna, Rantzer with  $T = 5$

$$dx = \begin{bmatrix} x_2 \\ -x_1 - x_2 - \frac{1}{2}x_1^3 \end{bmatrix} dt + \begin{bmatrix} 0 \\ 0.1 \end{bmatrix} dw.$$

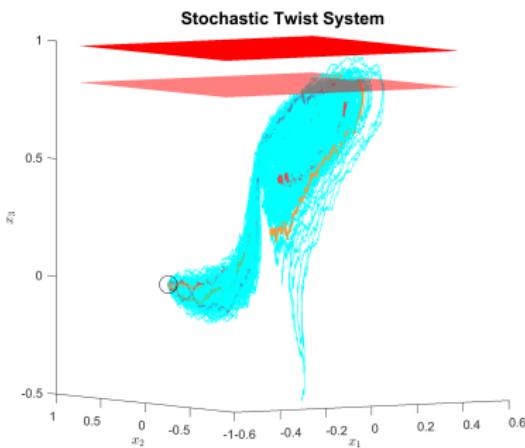


Maximize  $-x_2$  with  $d = 6$  (dashed=50%, solid=85% [ours])

# Three-State

Stochastic Twist system with  $T = 5$

$$dx = \begin{bmatrix} -2.5x_1 + x_2 - 0.5x_3 + 2x_1^3 + 2x_3^3 \\ -x_1 + 1.5x_2 + 0.5x_3 - 2x_2^3 - 2x_3^3 \\ 1.5x_1 + 2.5x_2 - 2x_3 - 2x_1^3 - 2x_2^3 \end{bmatrix} dt + \begin{bmatrix} 0 \\ 0 \\ 0.1 \end{bmatrix} dw.$$

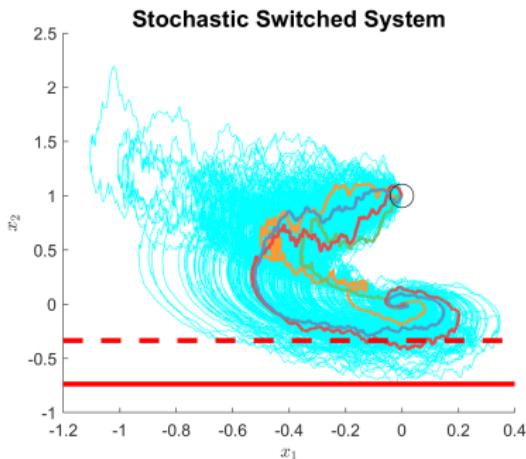


Maximize  $x_3$  with  $d = 6$  (translucent=50%, solid=85%)

# Two-State Switching

Switching subsystems at  $T = 5$

$$dx = \left\{ \begin{bmatrix} -2.5x_1 - 2x_2 \\ -0.5x_1 - x_2 \end{bmatrix}, \begin{bmatrix} -x_1 - 2x_2 \\ 2.5x_1 - x_2 \end{bmatrix} \right\} dt + \begin{bmatrix} 0 \\ 0.25x_2 \end{bmatrix} dw$$

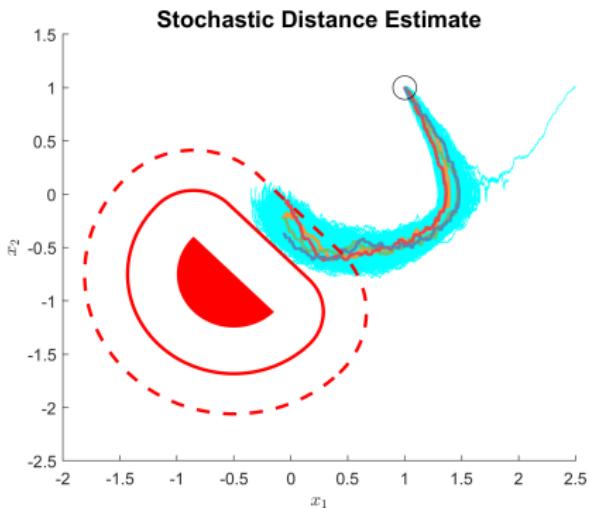


Maximize  $-x_2$  with  $d = 6$  (dashed=50%, solid=85%)

# Two-State Distance

Half-circle unsafe set  $X_u$

Based on distance estimation program



Minimize  $L_2$  distance to  $X_u$  with  $d = 6$  (dashed=50%, solid=85%)

# Time-Delay Peak Estimation

with M. Korda, V. Magron, M. Sznajer

---

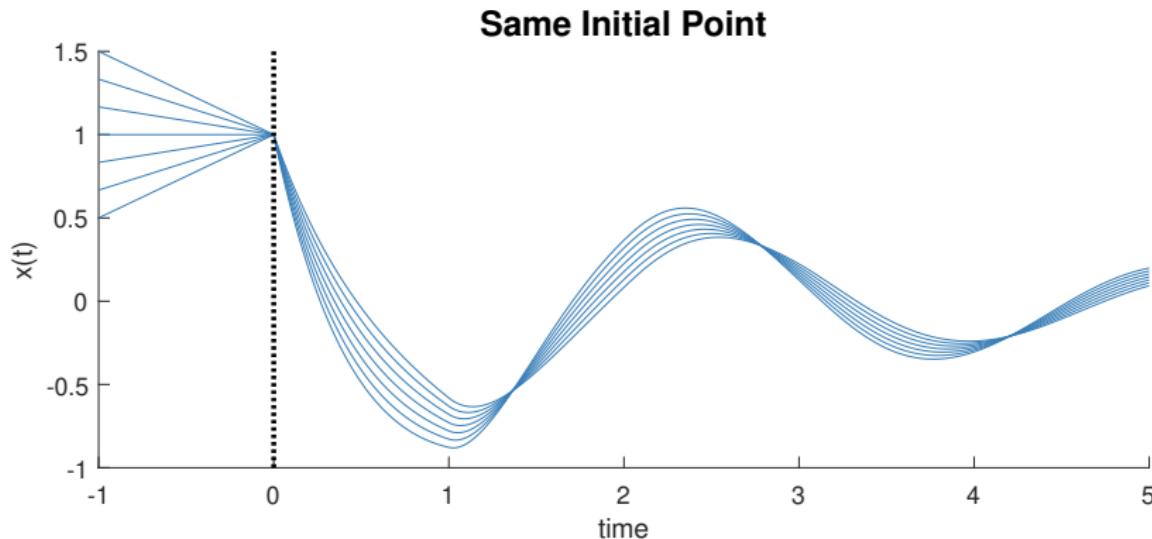
# Time-Delay Examples

Delay between state change and its effect on system

$$\begin{aligned}\dot{x}(t) &= f(t, x(t), x(t - \tau)) & \forall t \in [0, T] \\ x(s) &= x_h(s) & \forall s \in [-\tau, 0]\end{aligned}$$

System	Delay
Epidemic	Incubation Period
Population	Gestation Time
Traffic	Reaction Time
Congestion	Queue Time
Fluid Flow	Moving in Pipe

# Dependence on History



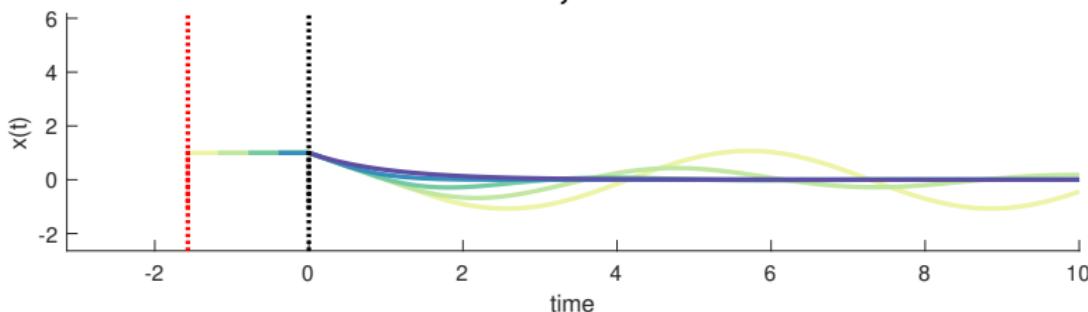
$$x'(t) = -2x(t) - 2x(t-1)$$

All trajectories pass through  $(t, x) = (0, 1)$

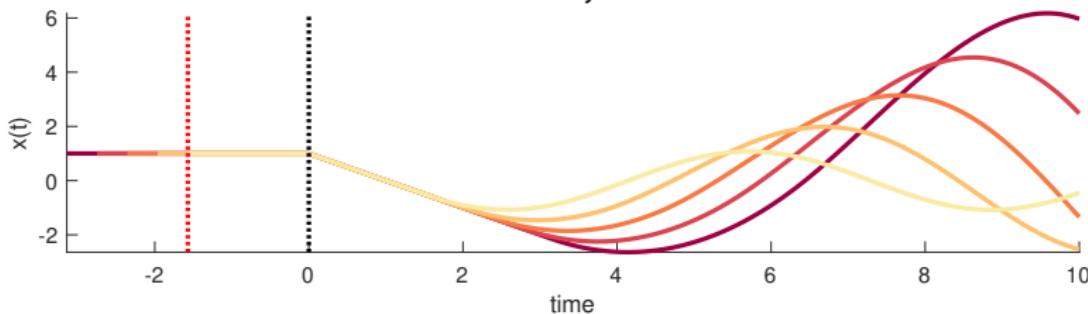
Initial history determines behavior, not just initial point

# Delay Bifurcation Example

**Stable,  $\tau < \pi/2$**

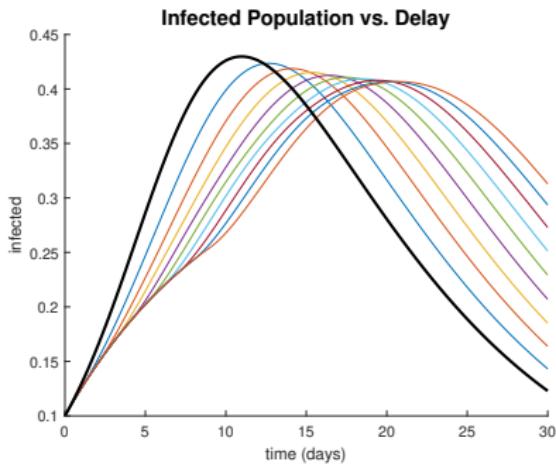


**Unstable,  $\tau > \pi/2$**

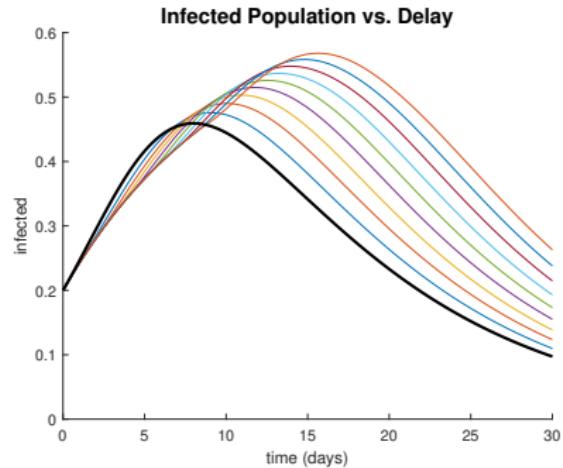


$$x'(t) = -x(t - \tau) \quad (\text{Fridman 2014})$$

# Peak Value vs. Delay



(a)  $I_h = 0.1$ , peak decreases



(b)  $I_h = 0.2$ , peak increases

$$\begin{bmatrix} S'(t) \\ I'(t) \end{bmatrix} = \begin{bmatrix} -0.4S(t)I(t) \\ 0.4S(t-\tau)I(t-\tau) - 0.1I(t) \end{bmatrix}$$

# Peak Estimation of Time-Delay Systems

History  $x_h(t)$  resides in a class of functions  $\mathcal{H}$

Graph-constrained  $\mathcal{H} : (t, x_h(t))$  contained in  $H_0 \subset [-\tau, 0] \times X$

$$P^* = \sup_{t^*, \textcolor{red}{x}_h} p(x(t^*))$$

$$\dot{x} = f(t, x(t), \textcolor{red}{x}(t - \tau)) \quad t \in [0, t^*]$$

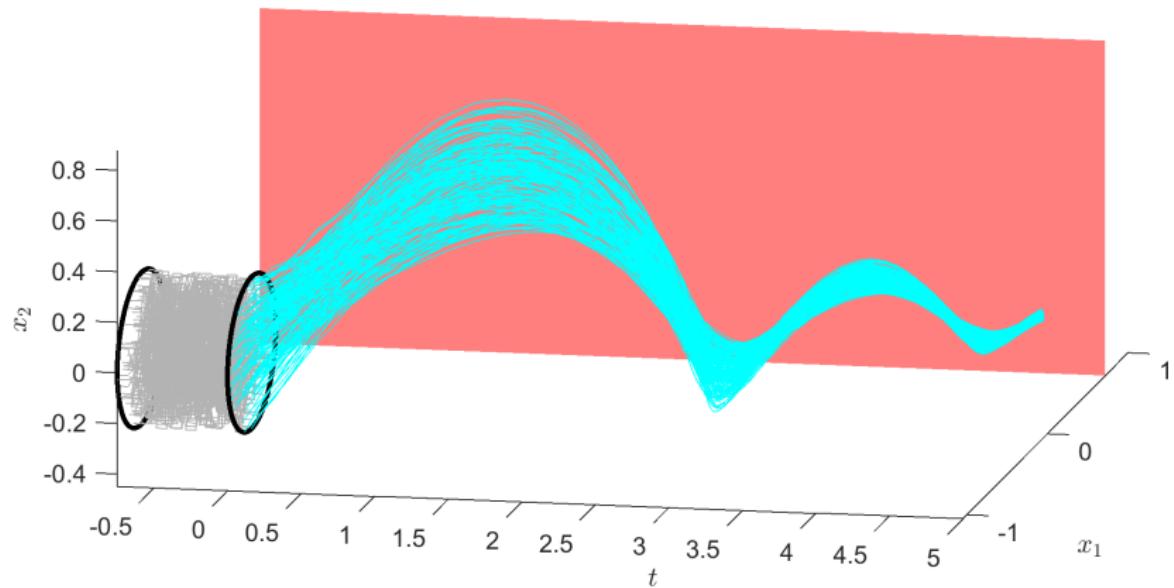
$$x(t) = x_h(t) \quad t \in [-\tau, 0]$$

$$\textcolor{red}{x}_h(\cdot) \in \mathcal{H}$$

Represent  $x(t | x_h) : t \in [-\tau, t^*]$  as occupation measure

# Time-Varying Preview

Order 5 bound: 0.71826



$$\text{Maximize } x_1 \text{ on } \dot{x}(t) = \begin{bmatrix} x_2(t)t - 0.1x_1(t) - x_1(t-\tau)x_2(t-\tau) \\ -x_1(t)t - x_2(t) + x_1(t)x_1(t-\tau) \end{bmatrix}$$

# Existing Methods (very brief)

---

## Certificates of Stability

- Lyapunov-Krasovskii
- Razumikhin
- LMI, Wirtinger
- ODE-Transport PDE

Relaxed control (Warga 1974, Vinter and Rosenblueth 1991-2)

Fixed-terminal-time OCP with gridding (Barati 2012)

SOS Barrier (Papachristodoulou and Peet, 2010)

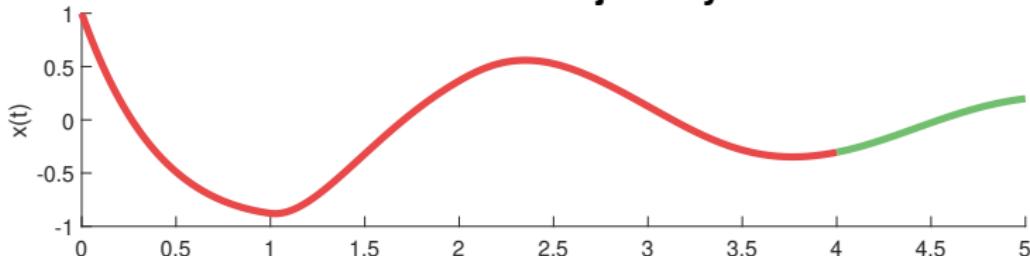
Riesz Operators (Magron and Prieur, 2020)

# Time-Delay Measure Program

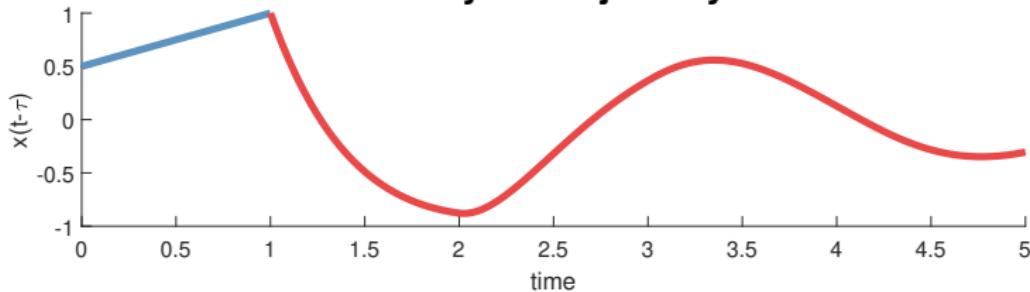
---

# Time-Delay Visualization

**Current Trajectory**



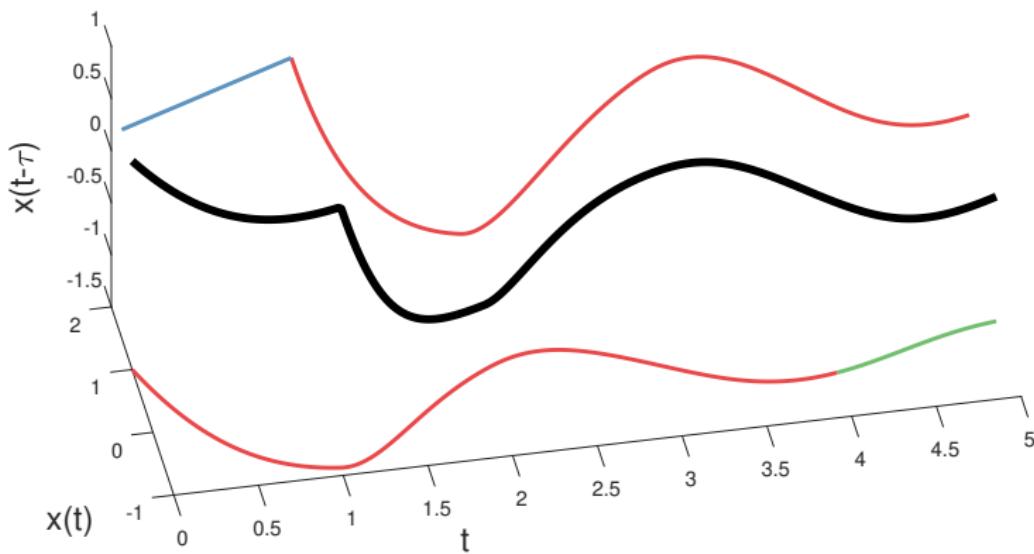
**Delayed Trajectory**



$$x(t) = -2x(t) - 2x(t-1), \quad x_h(t) = 1 - t/2$$

# Time-Delay Embedding

## Delay Embedding



Black curve:  $(t, x(t), x(t - \tau))$

# Measure-Valued Solution

Tuple of measures for the delayed case

Peak	$\mu_p \in \mathcal{M}_+([0, T] \times X)$
Initial	$\mu_0 \in \mathcal{M}_+(X_0)$
History	$\mu_h \in \mathcal{M}_+(H_0)$
Occupation Start	$\bar{\mu}_0 \in \mathcal{M}_+([0, T - \tau] \times X^2)$
Occupation End	$\bar{\mu}_1 \in \mathcal{M}_+([T - \tau, T] \times X^2)$
Time-Slack	$\nu \in \mathcal{M}_+([0, T] \times X)$

# Types of Constraints

---

Initial Conditions

Liouville: Dynamics

Consistency: Time-delay overlaps

# Initial Conditions

---

Point evaluation  $\langle 1, \mu_0 \rangle = 1$  at time  $t = 0^+$

History  $(t, x_h(t))$  defines a curve  $[-\tau, 0]$ , point at  $x_h(0)$

$t$ -marginal of  $\mu_h$  should be the Lebesgue measure in  $[-\tau, 0]$

Treat  $x(t - \tau) = x_1$  as an external input  $\dot{x}_0 = f(t, x_0, x_1)$

Sum  $\bar{\mu} = \bar{\mu}_0 + \bar{\mu}_1$  in times  $[0, T - \tau] \cap [T - \tau, T] = [0, T]$

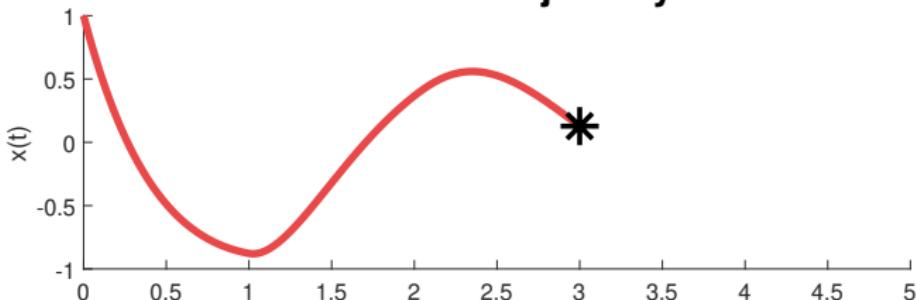
Based on the delay embedding  $(t, x(t), x(t - \tau))$

For all test functions  $v \in C^1([0, T] \times X)$ :

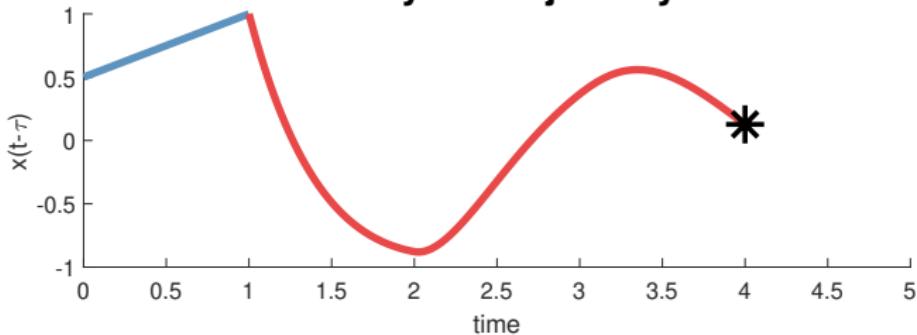
$$\langle v, \mu_p \rangle = \langle v(0, x), \mu_0(x) \rangle + \langle \mathcal{L}_{f(t, x_0, x_1)} v(t, x_0), \bar{\mu}(t, x_0, x_1) \rangle$$

# Consistency Issue

**Current Trajectory**



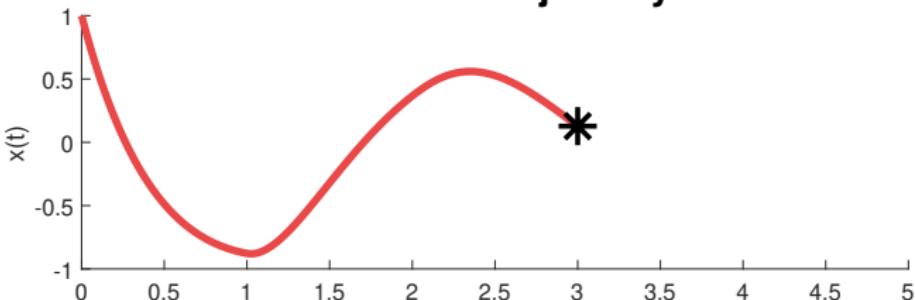
**Delayed Trajectory**



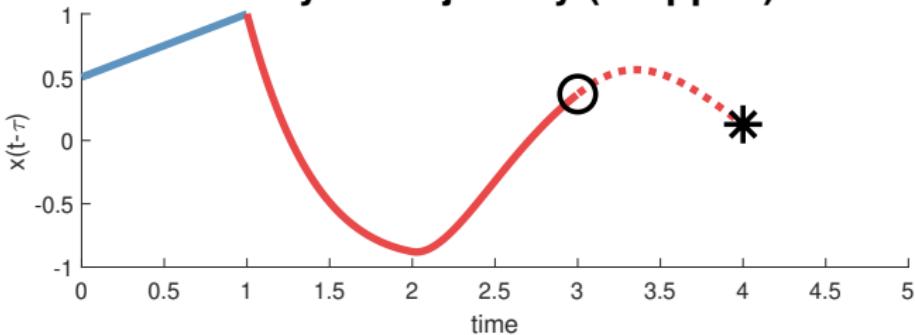
Inconsistent elapsed times

# Consistency Fix

**Current Trajectory**



**Delayed Trajectory (Stopped)**



Early stopping in delayed time

# Consistency Constraint

Inspired by changing limits of integrals  $t' \leftarrow t - \tau$

$$\begin{aligned} & \left( \int_0^{t^*} + \int_{t^*}^{\min(T, t^* + \tau)} \right) \phi(t, x(t - \tau)) dt \\ &= \left( \int_{-\tau}^0 + \int_0^{\min(t^*, T - \tau)} \right) \phi(t' + \tau, x(t')) dt'. \end{aligned}$$

Shift-push  $S_\#^\tau$  with  $\langle \phi, S_\#^\tau \mu \rangle = \langle S^\tau \phi, \mu \rangle = \langle \phi(t + \tau, x), \mu \rangle$

Consistency constraint with time-slack  $\nu$

$$\pi_\#^{tx_1}(\bar{\mu}_0 + \bar{\mu}_1) + \nu = S_\#^\tau(\mu_h + \pi_\#^{tx_0}\bar{\mu}_0).$$

# Measure Linear Program

Linear program for time-delay peak estimation

$$p^* = \sup \langle p, \mu_p \rangle \quad (8a)$$

$$\text{History-Validity}(\mu_0, \mu_h) \quad (8b)$$

$$\text{Liouville}(\mu_0, \mu_p, \bar{\mu}_0, \bar{\mu}_1) \quad (8c)$$

$$\text{Consistency}(\mu_h, \bar{\mu}_0, \bar{\mu}_1, \nu) \quad (8d)$$

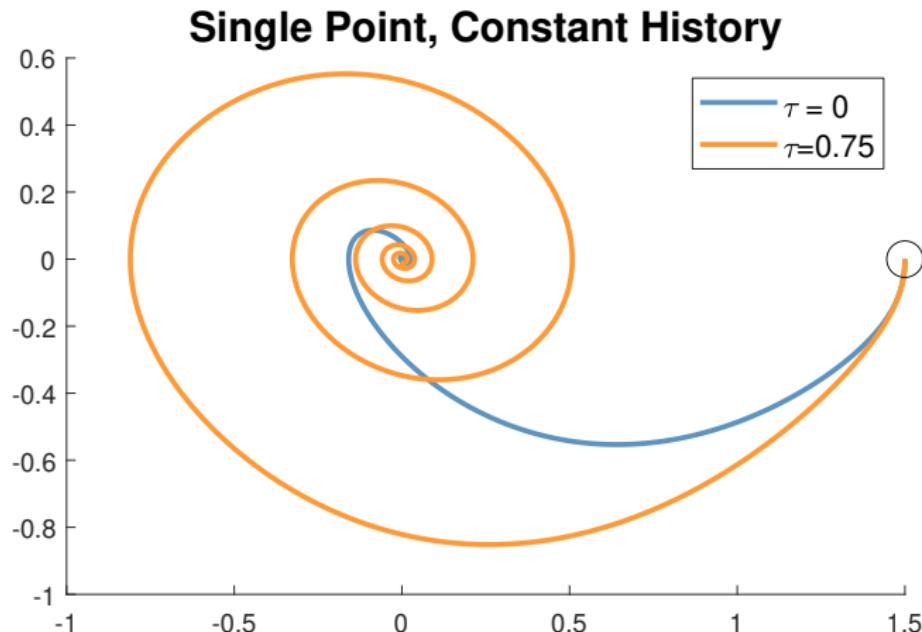
$$\text{Measure Definitions for } (\mu_h, \mu_0, \mu_p, \bar{\mu}_0, \bar{\mu}_1, \nu) \quad (8e)$$

Largest measures  $\bar{\mu}_0, \bar{\mu}_1$  have  $2n + 1$  variables

## Time-Delay Examples

---

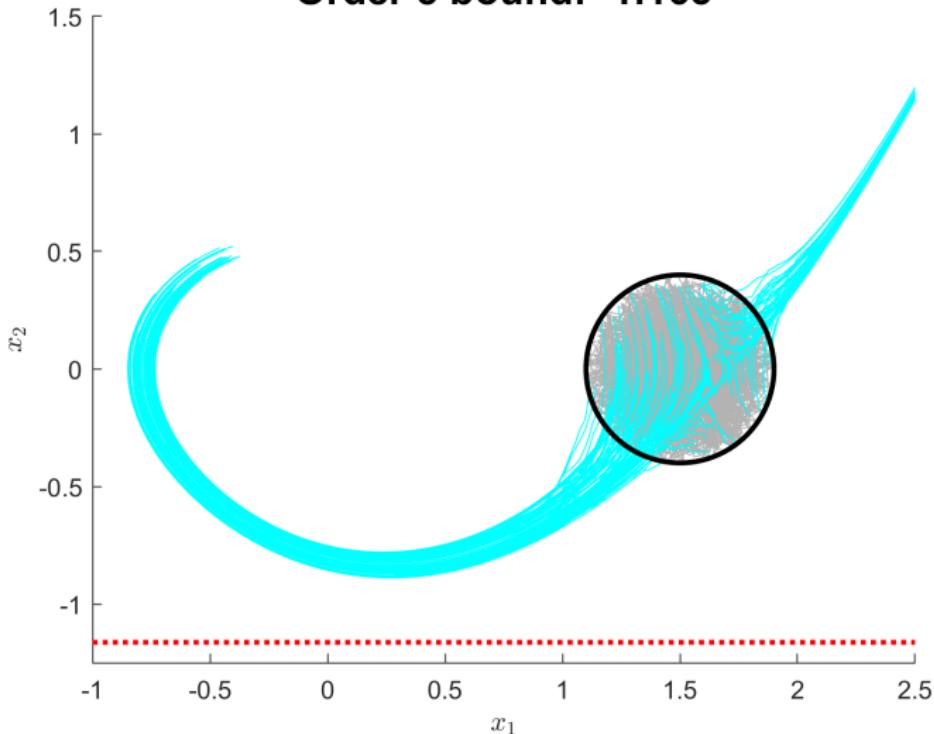
# Delay Comparison



$$\dot{x}(t) = \begin{bmatrix} x_2 \\ -x_1(t - \tau) - x_2(t) + x_1(t)^3/3 \end{bmatrix}$$

# Delayed Flow System

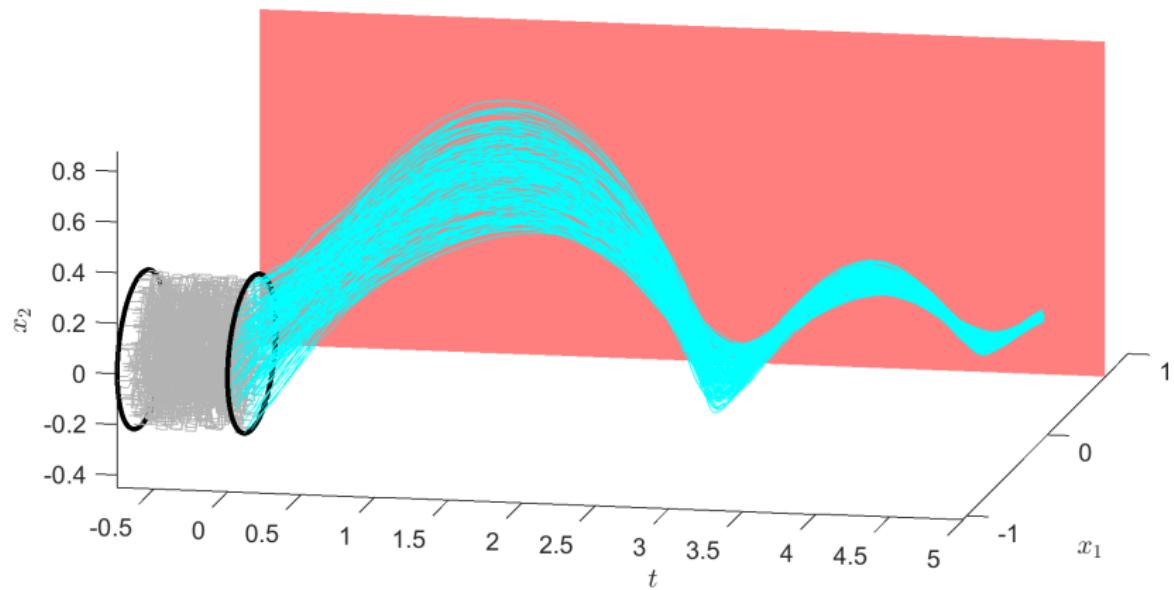
Order 5 bound: -1.163



Minimize  $x_2$  on the delayed Flow system

# Time-Varying System (Reprise)

Order 5 bound: 0.71826



$$\text{Maximize } x_1 \text{ on } \dot{x}(t) = \begin{bmatrix} x_2(t)t - 0.1x_1(t) - x_1(t-\tau)x_2(t-\tau) \\ -x_1(t)t - x_2(t) + x_1(t)x_1(t-\tau) \end{bmatrix}$$

## Take-aways

---

## Summary

---

Noted importance of safety quantification

Extended occupation measure methods for peak estimation

Performed data-driven analysis using robust counterparts

Adapted to non-ODE systems (Hybrid, SDE, Time-Delay)

## Future Work

---

- No-relaxation-gap for chance-peak and time-delay system
- High-order concentration inequalities
- Other time-delay models
- Lévy processes, Poisson jumps
- Distance-maximizing control
- Increased scalability, robotic systems
- Real-time computation

# Safety is Important



## Quantify using Peak Estimation

# Journal Papers

---

Published:

1. J. Miller, D. Henrion, and M. Sznajer, "Peak Estimation Recovery and Safety Analysis," *IEEE Control Systems Letters*, vol. 5, no. 6, pp. 1982–1987, 2021 [[link](#)]

Conditionally Accepted:

1. J. Miller and M. Sznajer, "Bounding the Distance to Unsafe Sets with Convex Optimization," (Conditionally accepted by IEEE Transactions on Automatic Control in 2022) [[link](#)]

# Conference Proceedings

---

1. J. Miller and M. Sznajer, "Bounding the Distance of Closest Approach to Unsafe Sets with Occupation Measures," in *2022 61st IEEE Conference on Decision and Control (CDC)*, pp. 5008–5013, 2022. [[link](#)]
2. J. Miller and M. Sznajer, "Facial Input Decompositions for Robust Peak Estimation under Polyhedral Uncertainty," *IFAC PapersOnLine*, vol. 55, no. 25, pp. 55–60, 2022. [[link](#)]. **IFAC Young Author Award (ROCOND)**
3. J. Miller, D. Henrion, M. Sznajer, and M. Korda, "Peak Estimation for Uncertain and Switched Systems," in *2021 60th IEEE Conference on Decision and Control (CDC)*, pp. 3222–3228, 2021. [[link](#)]. **Outstanding Student Paper Award (CDC 2021)**

# Preprints

---

1. J. Miller, M. Korda, V. Magron, and M. Sznaier “Peak Estimation of Time Delay Systems using Occupation Measures,” 2023. [link]
2. J. Miller, M. Tacchi, M. Sznaier, and A. Jasour, “Peak Value-at-Risk Estimation for Stochastic Differential Equations using Occupation Measures,” 2023. [link]
3. J. Miller and M. Sznaier, “Peak Estimation of Hybrid Systems with Convex Optimization,” 2023. [link]
4. J. Miller and M. Sznaier “Quantifying the Safety of Trajectories using Peak-Minimizing Control,” 2023. [link]
5. J. Miller and M. Sznaier, “Analysis and Control of Input-Affine Dynamical Systems using Infinite-Dimensional Robust Counterparts,” 2023. [link]

# Acknowledgements

---

Parents (Wayne and Debbie) and Family

Mario Sznaier, Octavia Camps, RSL

Didier Henrion, POP and MAC groups at LAAS-CNRS

Roy Smith, IfA at ETH Zurich

Jesús A. De Loera, ICERM

Fred Leve, Air Force Office of Scientific Research

Chateaubriand Fellowship of the Office for Science Technology  
of the Embassy of France in the United States.

National Science Foundation, Office of Naval Research

# Last but not least



The Warden

**Thank you again for your attention**



**Thank you again for your attention**

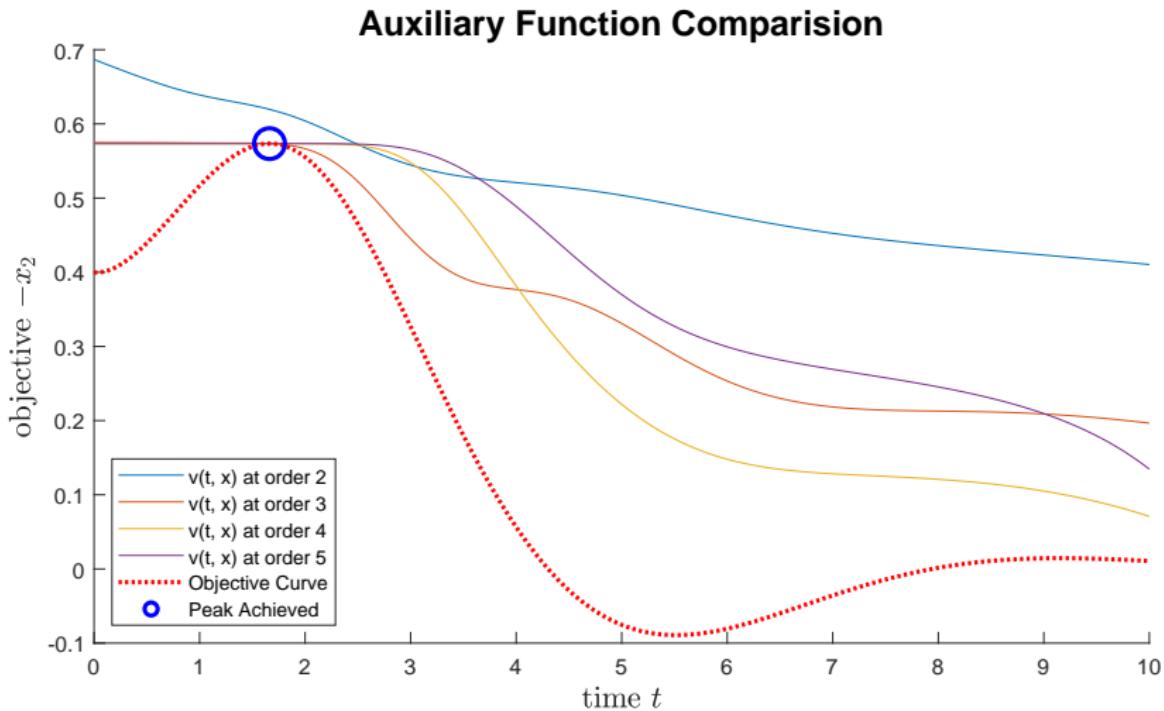


**Cookies in Dana 429 (RSL)**

## Bonus: Data-Driven Program

---

# Auxiliary Evaluation along Optimal Trajectory



Optimal  $v(t, x)$  should be constant until peak is achieved

# Noise Constraints

---

Polytopic region for  $L_\infty$ -bounded noise

2 linear constraints for each coordinate  $i$ , sample  $j$

$$-\epsilon \leq f_0(t_j, x_j)_i + \sum_{\ell=1}^L w_\ell f_\ell(t_j, x_j)_i - (\dot{x}_j)_i \leq \epsilon$$

Intersection of ellipsoids for  $L_2$ -bounded noise

$$\|f_0(t_j, x_j) + \sum_{\ell=1}^L w_\ell f_\ell(t_j, x_j) - (\dot{x}_j)\|_2 \leq \epsilon$$

# Robust Counterpart Theory

Semidefinite-representable uncertainty set

$$W = \cap_s \{ \exists \lambda_s \in \mathbb{R}^{q_s} : A_s w + G_s \lambda_s + e_s \in K_s \}$$

Lie constraint (based on Ben-Tal, Nemirovskii, 2009)

$$\mathcal{L}_f v(t, x, w) \leq 0 \quad \forall (t, x, w) \in [0, T] \times X \times W.$$

Nonconservative robust counterpart with multipliers  $\zeta$

$$\mathcal{L}_{f_0} v(t, x) + \sum_{s=1}^{N_s} e_s^T \zeta_s(t, x) \leq 0 \quad \forall [0, T] \times X$$

$$G_s^T \zeta_s(t, x) = 0 \quad \forall s = 1..N_s$$

$$\sum_{s=1}^{N_s} (A_s^T \zeta_s(t, x))_\ell + f_\ell(t, x) \cdot \nabla_x v(t, x) = 0 \quad \forall \ell = 1..L$$

$$\zeta_s(t, x) \in K_s^* \quad \forall s = 1..N_s$$

# Peak Decomposed Program

Example: Polytopic uncertainty  $W = \{w \mid Aw \leq b\}$

Only the Lie Derivative constraint changes

$$d^* = \min_{\gamma \in \mathbb{R}} \gamma$$

$$\gamma \geq v(0, x) \quad \forall x \in X_0$$

$$\mathcal{L}_{f_0} v(t, x) + b^T \zeta(t, x) \leq 0 \quad \forall (t, x) \in [0, T] \times X$$

$$(A^T)_\ell \zeta(t, x) = (f_\ell \cdot \nabla_x) v(t, x) \quad \forall \ell = 1..L$$

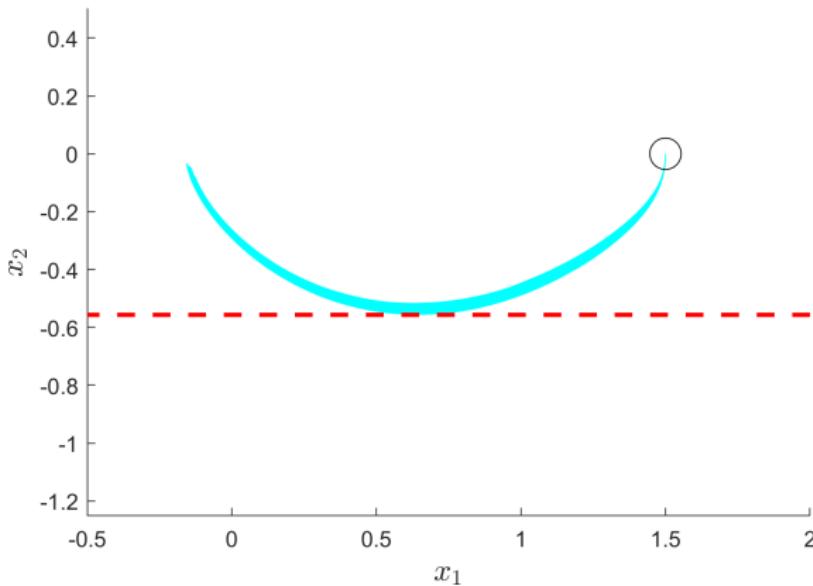
$$v(t, x) \geq p(x) \quad \forall (t, x) \in [0, T] \times X$$

$$v(t, x) \in C^1([0, T] \times X)$$

$$\zeta_k(t, x) \in C_+([0, T] \times X) \quad \forall k = 1..m$$

# Peak Estimation Example (Flow)

Order 4 bound = 0.557

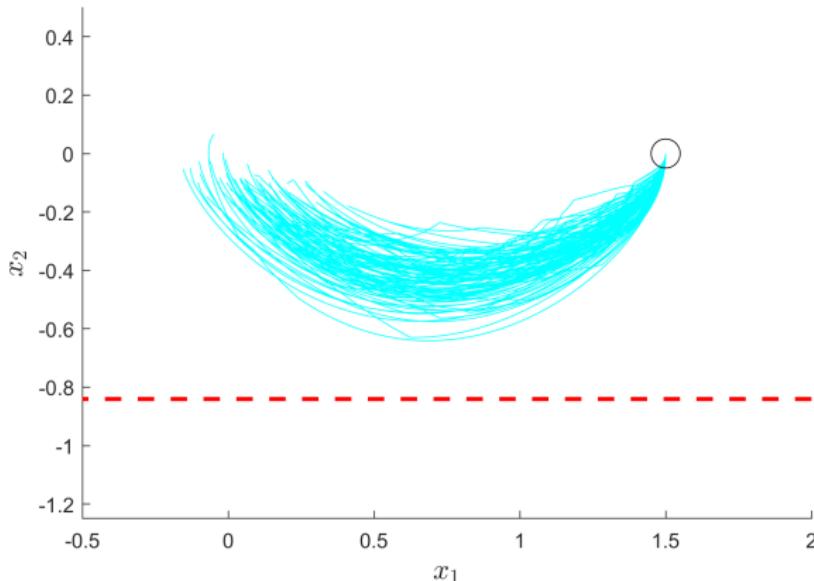


$$\dot{x} = [x_2, -wx_1 - x_2 + x_1^3/3]$$

$$L = 1, m = 80 \text{ (2 nonredundant)}$$

# Peak Estimation Example (Flow)

Order 4 bound = 0.841



$$\dot{x} = [x_2, \text{cubic}(x_1, x_2)]$$

$$L = 10, m = 80 \text{ (33 nonredundant)}$$

# Crash-Bound Program

Consistency sets

$$Z = [0, J_{\max}] \quad \Omega = \{(w, z) \in W \times Z : J(w) \leq z\}.$$

Optimal Control Problem with auxiliary  $v(t, x, z) \in C^1$

$$d^* = \sup_{\gamma \in \mathbb{R}, v} \gamma$$

$$v(0, x, z) \geq \gamma \quad \forall (x, z) \in X_0 \times Z$$

$$v(t, x, z) \leq z \quad \forall (t, x, z) \in [0, T] \times X_u \times Z$$

$$\mathcal{L}_f v(t, x, z, w) \geq 0 \quad \forall (t, x, z, w) \in [0, T] \times X \times \Omega$$

# Crash Lie-decomposition

Exploit affine structure of  $J(w) = \|\Gamma w - h\|_\infty$

Nonconservatively robustified Lie constraint

$$d^* = \sup_{\gamma \in \mathbb{R}, v} \gamma$$

$$v(0, x, z) \geq \gamma \quad \forall (x, z) \in X_0 \times Z$$

$$v(t, x, z) \leq z \quad \forall (t, x, z) \in [0, T] \times X_u \times Z$$

$$\mathcal{L}_{f_0} v - (z\mathbf{1} + h)^T \zeta \geq 0 \quad \forall (t, x, z) \in [0, T] \times X \times [0, J_{\max}]$$

$$(\Gamma^T)_{\ell} \zeta + f_{\ell} \cdot \nabla_x v = 0 \quad \forall \ell = 1..L$$

$$\zeta_j \in C_+([0, T] \times X \times Z) \quad \forall j = 1..2nT.$$

# Sum-of-Squares Method

---

Every  $c \in \mathbb{R}$  satisfies  $c^2 \geq 0$

Sufficient:  $q(x) \in \mathbb{R}[x]$  nonnegative if  $q(x) = \sum_i q_i^2(x)$

Exists  $v(x) \in \mathbb{R}[x]^s$ , Gram matrix  $Z \in \mathbb{S}_+^s$  with  $q = v^T Z v$

Sum-of-Squares (SOS) cone  $\Sigma[x]$

$$\begin{aligned} & x^2y^4 - 6x^2y^2 + 10x^2 + 2xy^2 + 4xy - 6x + 4y^2 + 1 \\ &= (x + 2y)^2 + (3x - 1 - xy^2)^2 \end{aligned}$$

Motzkin Counterexample (nonnegative but not SOS)

$$x^2y^4 + x^4y^2 - x^2y^2 + 1$$

## Sum-of-Squares Method (cont.)

---

Putinar Positivstellensatz (Psatz) nonnegativity certificate over set  $\mathbb{K} = \{x \mid g_i(x) \geq 0, h_j(x) = 0\}$ :

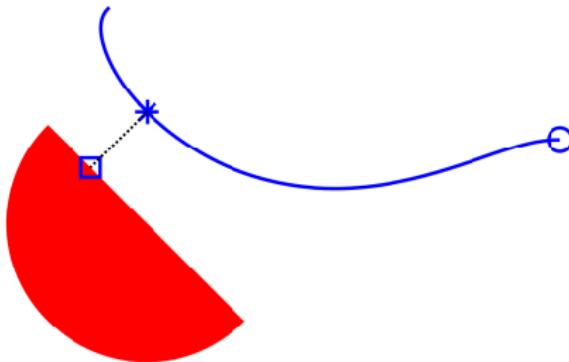
$$q(x) = \sigma_0(x) + \sum_i \sigma_i(x)g_i(x) + \sum_j \phi_j(x)h_j(x) \quad (9a)$$

$$\exists \sigma_0(x) \in \Sigma[x], \quad \sigma_i(x) \in \Sigma[x], \quad \phi_j \in \mathbb{R}[x]. \quad (9b)$$

Psatz at degree  $2d$  is an SDP, monomial basis:  $s = \binom{n+d}{d}$

Archimedean:  $\exists R \geq 0$  where  $R - \|x\|_2^2$  has Psatz over  $\mathbb{K}$

# Optimal Trajectories (Distance)



Optimal trajectories described by  $(x_p^*, y^*, x_0^*, t_p^*)$ :

- $x_p^*$  location on trajectory of closest approach
- $y^*$  location on unsafe set of closest approach
- $x_0^*$  initial condition to produce  $x_p^*$
- $t_p^*$  time to reach  $x_p^*$  from  $x_0^*$

# Measures from Optimal Trajectories

---

Form measures from each  $(x_p^*, x_0^*, t_p^*, y^*)$

Atomic Measures (rank-1)

$$\mu_0^* : \quad \delta_{x=x_0^*}$$

$$\mu_p^* : \quad \delta_{t=t_p^*} \otimes \delta_{x=x_p^*}$$

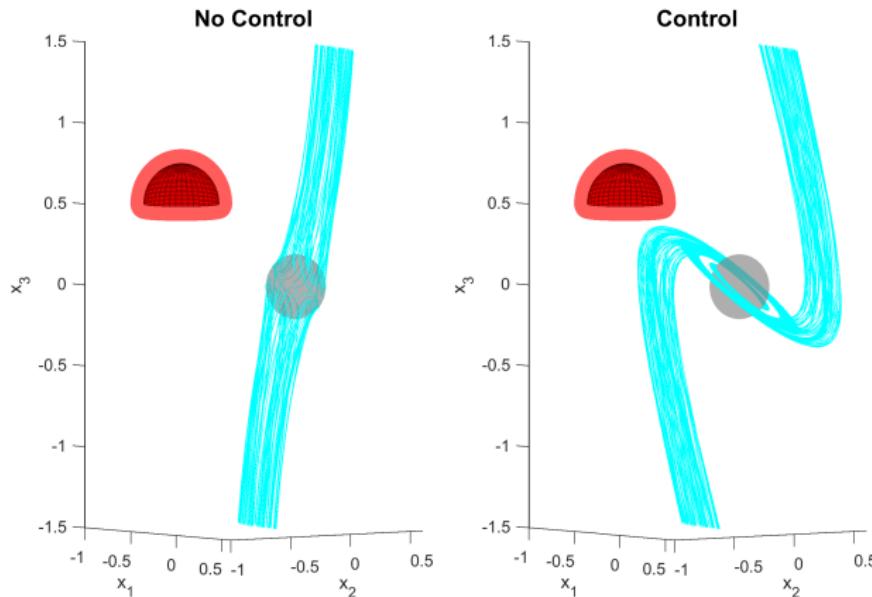
$$\eta^* : \quad \delta_{x=x_p^*} \otimes \delta_{y=y^*}$$

Occupation Measure       $\forall v(t, x) \in C([0, T] \times X)$

$$\mu^* : \quad \langle v(t, x), \mu \rangle = \int_0^{t_p^*} v(t, x^*(t | x_0^*)) dt$$

# Hybrid Systems

## State guards and transitions



$L_2$  bound 0.0891: uncontrolled to boundary, controlled to sphere

## Bonus: Chance-Peak

---

# Second-Order Cone Program

Reformulate as infinite-dimensional second-order cone program

$$\text{SOC set } Q^3 = \{(s, \kappa) \in \mathbb{R}^3 \times \mathbb{R}_{\geq 0} \mid \|s\|_2 \leq \kappa\}$$

$$p_r^* = \sup_{z \in \mathbb{R}} \quad r z + \langle p, \mu_\tau \rangle \tag{10a}$$

$$\mu_\tau = \delta_0 \otimes \mu_0 + \mathcal{L}^\dagger \mu \tag{10b}$$

$$s = [1 - \langle p^2, \mu_\tau \rangle, 2z, 2\langle p, \mu_\tau \rangle] \tag{10c}$$

$$(s, 1 + \langle p^2, \mu_\tau \rangle) \in Q^3 \tag{10d}$$

$$\mu, \mu_\tau \in \mathcal{M}_+([0, T] \times X). \tag{10e}$$

Moment-SOS:  $p_d^* \geq p_{d+1}^* \geq \dots \geq p_r^* = P_r^* \geq P^*$

## Bonus: Time Delay

---

# Computational Complexity

Use moment-SOS hierarchy (Archimedean assumption)

Degree  $d$ , dynamics degree  $\tilde{d} = d + \max(\lfloor \deg f/2 \rfloor, \deg g - 1)$

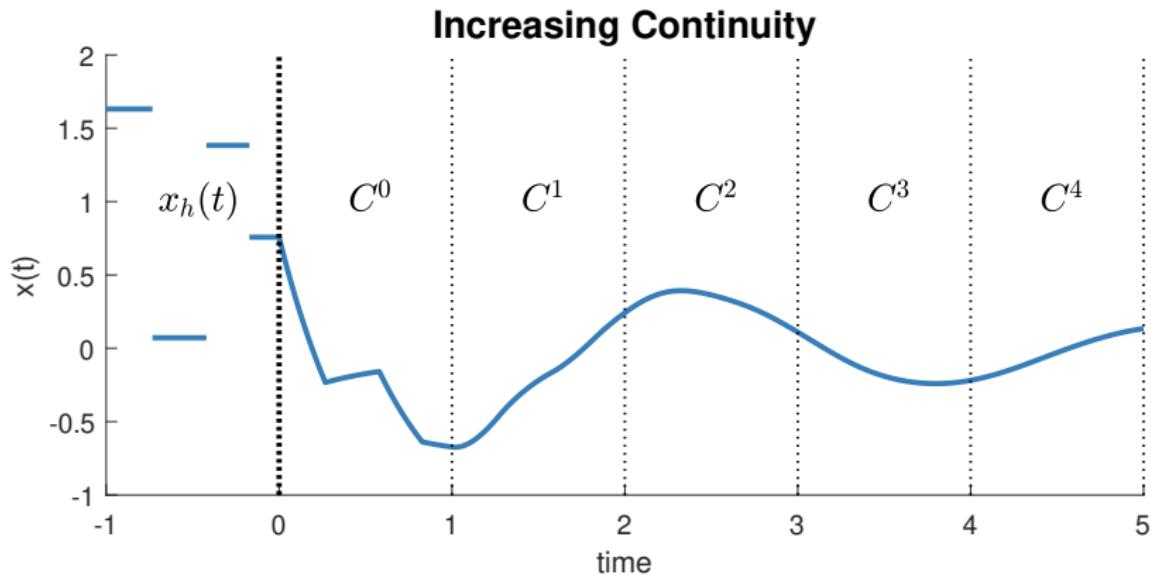
Bounds:  $p_d^* \geq p_{d+1}^* \geq \dots \geq p_r^* = P_r^* \geq P^*$

Measure     $\mu_p(t, x)$      $\mu(t, x)$

PSD Size     $\binom{1+n+d}{d}$      $\binom{1+n+\tilde{d}}{\tilde{d}}$

Timing scales approximately as  $(1 + n)^{6\tilde{d}}$  or  $\tilde{d}^{4(n+1)}$

# Propagation of Continuity



$$x'(t) = -2x(t) - 2x(t-1)$$

Continuity increases every  $\tau_r$  time steps

# Computational Complexity

Use moment-SOS hierarchy (Archimedean assumption)

Degree  $d$ , dynamics degree  $\tilde{d} = d + \lfloor \deg f / 2 \rfloor$

Bounds:  $p_d^* \geq p_{d+1}^* \geq \dots = p^* \geq P^*$

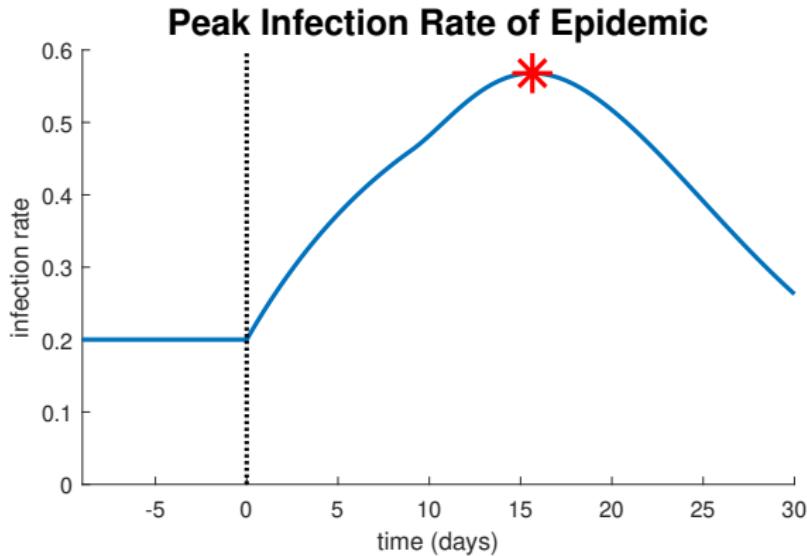
Size of Moment Matrices Peak Estimation

Measure:	$\mu_0$	$\mu^p$	$\mu_h$
Size:	$\binom{n+d}{d}$	$\binom{n+1+d}{d}$	$\binom{n+1+\tilde{d}}{\tilde{d}}$

Measure:	$\bar{\mu}_0$	$\bar{\mu}_1$	$\nu$
Size:	$\binom{2n+1+\tilde{d}}{\tilde{d}}$	$\binom{2n+1+\tilde{d}}{\tilde{d}}$	$\binom{n+1+\tilde{d}}{\tilde{d}}$

Timing scales approximately as  $(2n+1)^{6\tilde{d}}$  or  $\tilde{d}^{4(2n+1)}$

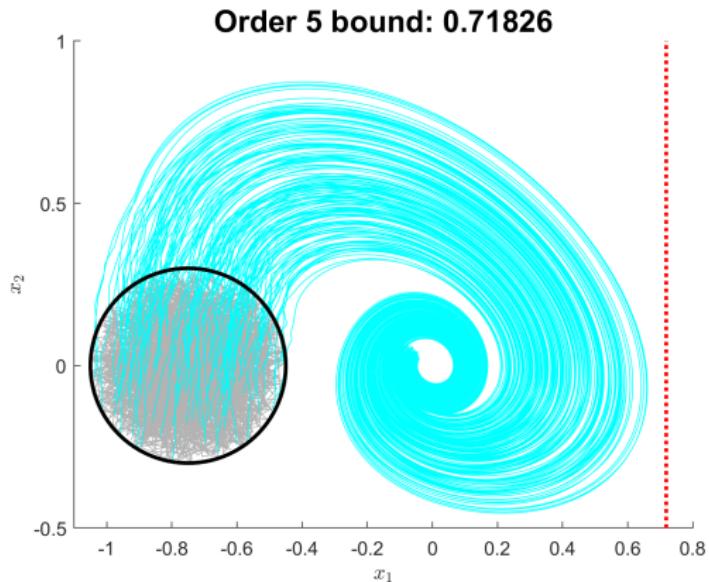
# SIR Peak Estimation Example



Upper bound  $I_{max} \geq 56.9\%$  with order 3 LMI

Recovery:  $t_* = 15.6$  days,  $(S^*, I^*) = (56.9\%, 5.61\%)$

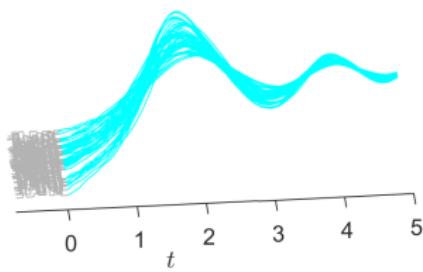
# Time-Varying System



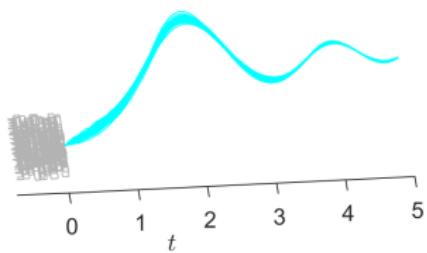
$$\text{Maximize } x_1 \text{ on } \dot{x}(t) = \begin{bmatrix} x_2(t)t - 0.1x_1(t) - x_1(t-\tau)x_2(t-\tau) \\ -x_1(t)t - x_2(t) + x_1(t)x_1(t-\tau) \end{bmatrix}$$

# Time-Varying Histories

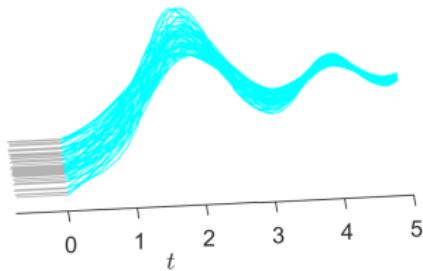
**Free**



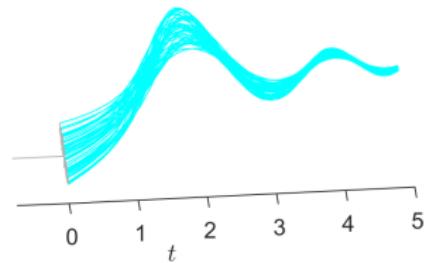
**Pinhole**



**Constant**



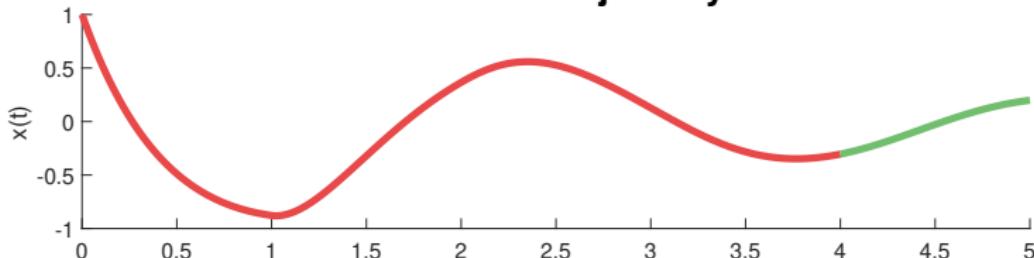
**Constant-Center Jump**



History restrictions and trajectories of system

# Joint+Component Consistency

## Current Trajectory

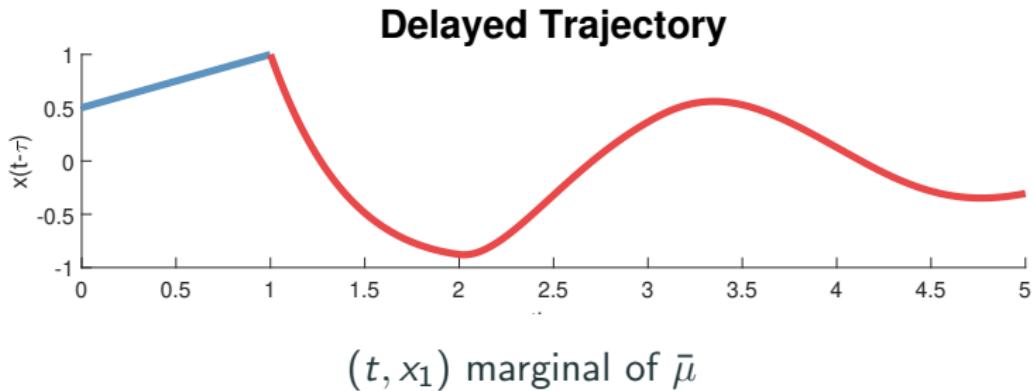


$(t, x_0)$  marginal of  $\bar{\mu}$

For all test functions  $\phi_0 \in C([0, T] \times X)$

$$\begin{aligned}\langle \phi_0(t, x_0), \bar{\mu} \rangle &= \int_0^T \phi_0(t, x(t | x_h)) dt \\ &= \left( \int_0^{T-\tau} + \int_{T-\tau}^T \right) \phi_0(t, x(t | x_h)) dt \\ &= \langle \phi_0(t, x), \nu_0 + \nu_1 \rangle\end{aligned}$$

# Joint+Component Consistency (cont.)



For all test functions  $\phi_1 \in C([0, T] \times X)$

$$\begin{aligned}\langle \phi_1(t, x_1), \bar{\mu} \rangle &= \int_0^T \phi_1(t, x(t - \tau \mid x_h)) dt \\ &= \int_{-\tau}^{T-\tau} \phi_1(t + \tau, x(t \mid x_h)) dt \\ &= \int_{-\tau}^0 \phi_1(t + \tau, \textcolor{blue}{x}_h(t)) dt + \langle \phi_1(t + \tau, x), \textcolor{red}{v}_0 \rangle\end{aligned}$$

# Joint+Component Experiment

**Table 1:** Objective values for Flow experiment

degree $d$	1	2	3	4	5
Joint+Component	1.25	1.223	1.1937	1.1751	1.1636
Standard	1.25	1.2183	1.1913	1.1727	1.1630

**Table 2:** Time (seconds) to obtain SDP bounds in Table 1

degree $d$	1	2	3	4	5
Joint+Component	0.782	0.991	5.271	31.885	336.509
Standard	0.937	1.190	9.508	105.777	552.496

## Bonus: Measure Background

---

# Measures

---

Nonnegative Borel Measure  $\mu$

Assigns each set  $A \subseteq X$  a 'size'  $\mu(A) \geq 0$  (Measure)

Mass  $\mu(X) = \langle 1, \mu \rangle = 1$ : Probability distribution

$\mu \in \mathcal{M}_+(X)$ : space of measures on  $X$

$f \in C(X)$ : continuous function on  $X$

Pairing by Lebesgue integration  $\langle f, \mu \rangle = \int_X f(x)d\mu(x)$

# Dirac Delta Measure

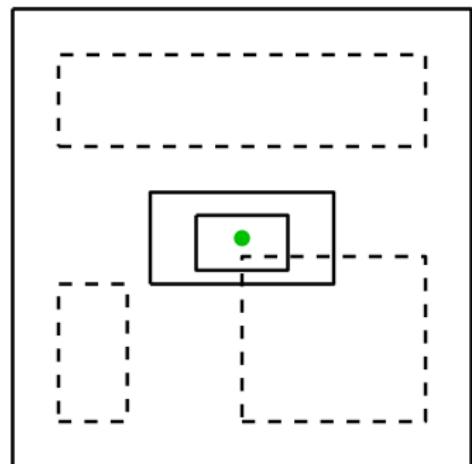
$$\text{Dirac delta } \delta_{x'}(A) = \begin{cases} 1 & x' \in A \\ 0 & x' \notin A \end{cases}$$

Probability:

$$\delta_{x'}(X) = 1, \langle f(x), \delta_{x'} \rangle = f(x')$$

$\mu(A) = 1$ : Solid Box

$\mu(A) = 0$ : Dashed Box



# Atomic Measure

---

Rank-1 atomic measure

$$\mu = c\delta_{x'} \quad c > 0$$

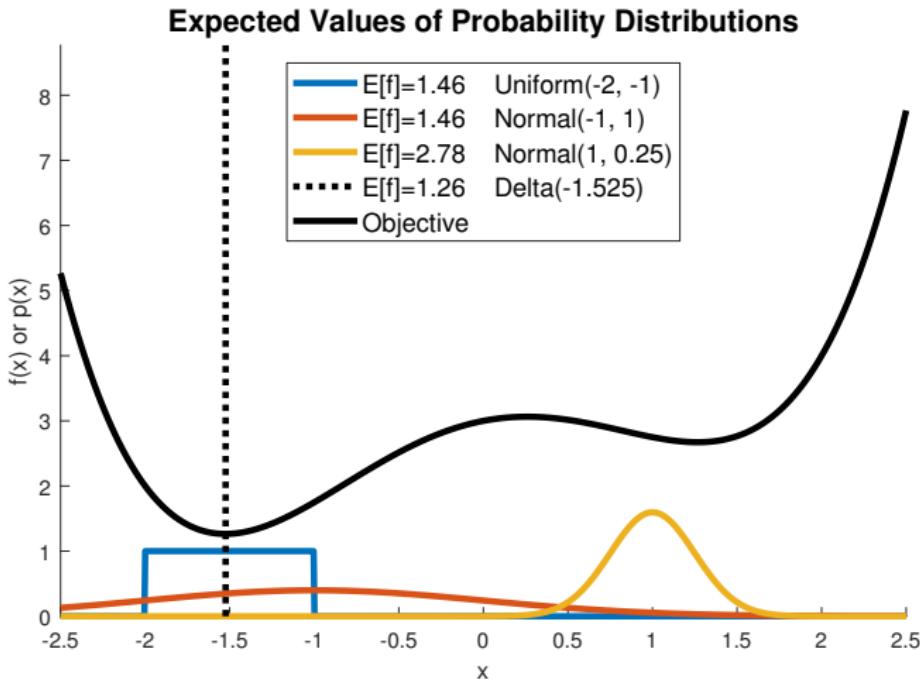
Rank-2 atomic measure

$$\mu = c_1\delta_{x'_1} + c_2\delta_{x'_2} \quad c > 0, \quad x'_1 \neq x'_2$$

Rank-r atomic measure

$$\mu = \sum_{i=1}^r c_i\delta_{x'_i} \quad c > 0, \quad \{x'_i\}_{i=1}^r \text{ distinct}$$

# Example of Measure Optimization

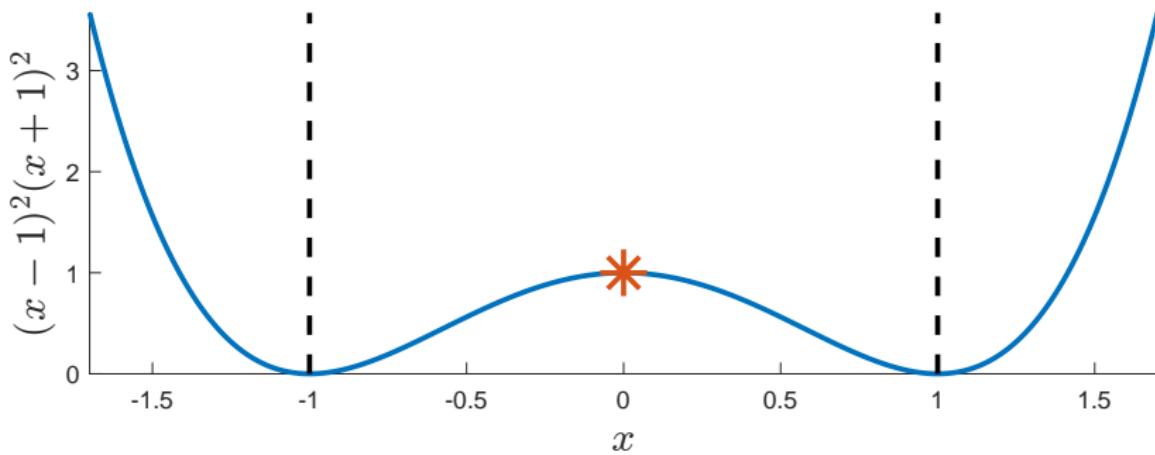


Optimum  $\mathbb{E}_\mu[f] = \langle f, \mu \rangle$  at  $\mu = \delta_{x^*}$

# Measure Optimization

Nonconvex problems could be convex in measures

$$\min_{x \in K} p(x) \rightarrow \min_{\mu \in \mathcal{M}_+(K)} \langle p, \mu \rangle, \quad \langle 1, \mu \rangle = 1$$



$$f\left(\frac{1}{2}(1 + (-1))\right) = 1, \text{ but } \frac{1}{2}(f(1) + f(-1)) = 0$$

## Bonus: Approximating Measure LPs

---

# Need for Approximation

---

Measure LPs are infinite-dimensional

Linear Matrix Inequality: convex problem

$$\max_y b^T y \quad C + \sum_{i=1}^m A_i y_i \geq 0$$

Solve LMIs through (interior point, ADMM, etc.)

Approximate infinite LPs by finite-dimensional LMIs

# Moments

---

Monomial  $x^\alpha = \prod_i x_i^{\alpha_i}$  for power  $\alpha \in \mathbb{N}^n$

Degree  $|\alpha| = \sum_i \alpha_i$

$\alpha$ -moment of measure  $y_\alpha = \langle y_\alpha, \mu \rangle$

Measure uniquely described by infinite set  $\{y_\alpha\}_{\alpha \in \mathbb{N}^n}$

When does a sequence  $\{y_\alpha\}_{\alpha \in \mathcal{A}}$  correspond to a measure  $\mu$ ?

# Linear Functional

---

Linear Functional polynomial → moments

$$f(x) \rightarrow \int_X f(x) d\mu = \int_X \sum_{\alpha} f_{\alpha} x^{\alpha} d\mu = \sum_{\alpha} f_{\alpha} y_{\alpha}$$

Bivariate Example

$$2 + x_1 x_2 - 3x_1^2 + x_1 x_2^3 \rightarrow 2 + y_{11} - 3y_{20} + y_{13}$$

# Moment Matrices

Squares  $f(x)^2$  are nonnegative (real)

$f(x)^2 \geq 0$  implies that  $\langle f(x)^2, \mu \rangle \geq 0 \quad \forall f \in \mathbb{R}[x]$ :

$$\langle f(x)^2, \mu \rangle = \int_X \sum_{\alpha, \beta} (f_\alpha x^\alpha)(f_\beta x^\beta) d\mu = \int_X \sum_{\alpha, \beta} (f_\alpha f_\beta x^{\alpha+\beta}) d\mu \geq 0$$

Moment matrix  $\mathbb{M}[y] \succeq 0$  has  $\mathbb{M}[y]_{\alpha, \beta} = y_{\alpha+\beta}$

$$\langle f(x)^2, \mu \rangle = \mathbf{f}^T \mathbb{M}[y] \mathbf{f} \geq 0$$

# Moment Matrix Example

Moments up to degree  $2 \times 2 = 4$

$$\mathbb{M}_2[y] = \begin{bmatrix} y_{00} & y_{10} & y_{01} & y_{20} & y_{11} & y_{02} \\ y_{10} & y_{20} & y_{11} & y_{30} & y_{21} & y_{12} \\ y_{01} & y_{11} & y_{02} & y_{21} & y_{12} & y_{03} \\ y_{20} & y_{30} & y_{21} & y_{40} & y_{31} & y_{11} \\ y_{11} & y_{21} & y_{12} & y_{31} & y_{22} & y_{13} \\ y_{02} & y_{12} & y_{03} & y_{22} & y_{13} & y_{04} \end{bmatrix}$$

# Localizing Matrices

$\mu$  supported on set  $K = \{x \mid g_i(x) \geq 0, i = 1 \dots N\}$

$g_i(x)f(x)^2 \geq 0$  implies that  $\langle g_i(x)f(x)^2, \mu \rangle \geq 0$

$$\langle g_i(x)f(x)^2, \mu \rangle = \int_X \sum_{\alpha, \beta, \gamma} (f_\alpha f_\beta g_\gamma x^{\alpha+\beta+\gamma}) d\mu \geq 0$$

Localizing matrix  $\mathbb{M}[g_i m] \succeq 0$  has  $\mathbb{M}[g_i m]_{\alpha, \beta} = \sum_{\gamma} g_\gamma m_{\alpha+\beta+\gamma}$

$$\langle g_i(x)f(x)^2, \mu \rangle = \mathbf{f}^T \mathbb{M}[g_i y] \mathbf{f} \geq 0$$

# Moment-SOS Hierarchy

Polynomial optimization problem example :

$$p^* = \max_{x \in K} p(x) = \max_{\mu \in \mathcal{M}_+(K)} \langle p(x), \mu \rangle, \quad \mu(K) = 1$$

Keep moments up to degree  $d$ :

$$\begin{aligned} p_d^* &= \max_y \sum_{|\alpha| \leq 2d} p_\alpha m_\alpha \\ \mathbb{M}_d[y], \quad \mathbb{M}_{d-\deg(g_i)}[g_i y] &\succeq 0 \end{aligned}$$

Finite-dimensional SDP:  $\mathbb{M}_d[y]$  has size  $\binom{n+d}{d}$

Bounds  $p_d^* \geq p_{d+1}^* \geq p_{d+2}^* \dots$  converge to  $p^*$  as  $d \rightarrow \infty$

# Approximation Pipeline

---

1. Trajectory Program
2. Measure LP
3. Moment LMI

Increase degree  $d$  of LMI to get better bounds

Prove conditions under which  $\lim_{d \rightarrow \infty} p_d^* \rightarrow p^* = P^*$